ESSAYS ON HUMAN CAPITAL AND ADVERSE SHOCKS

by

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Abstract

This dissertation examines the impact of adverse changes in the personal cost of building human capital on individuals' choices with regard to employment and education, as well as market reactions to that impact. In my first and third chapters, I focus on child care as a significant cost of employment, examining the effects of reducing that cost via public subsidy on employment stability for recipient and non-recipient women and wage outcomes for female workers overall. In my second chapter, I look at high school students' decisions regarding postsecondary education, incorporating their possible concerns about adverse events that could derail their educational progress.

In the first chapter, "Female Unemployment and Statistical Discrimination: The Revealing Effects Child Care Subsidies," I examine the effects of child care subsidies on female employment, including potential spillover effects on those without children, which can occur in the presence of limited information and statistical discrimination. I provide evidence from the Survey of Income and Program Participation (SIPP) that working mothers quit their jobs less often and childless women in low-wage occupations experience layoffs less frequently where child care subsidies are more generous. To rationalize these patterns, I develop a labor search and matching model that incorporates statistical discrimination and a firm cost of separation from employees. Estimates from the search model allow me to examine counterfactual scenarios which reveal that changes in discriminatory behavior by firms can generate an economically significant spillover effect outside a policy's target population.

In my second chapter, "Rational Responses to Uncertainty? Understanding Disadvantaged Youths' Educational Choices," my coauthors (Stefanie DeLuca, Seth Gershenson, and Nicholas Papageorge) and I investigate a heretofore overlooked reason that youths from historically disadvantaged backgrounds might underinvest in education: their experiences of instability. If youths correctly anticipate adverse shocks that will interrupt their educational pursuits, then avoiding the time commitment associated with obtaining a four-year degree is a rational decision. We examine this possibility using nationally-representative data sets, and propose the future collection of more narrowly focused data for the purpose of analyzing the frequency of such shocks and their effect on educational choices and outcomes. We also formulate a structural model which both informs the survey design process and will allow us to predict the effects policies designed to mitigate educational derailment.

I expand on my model of job search in the third chapter, "Involuntary Quits, Bargaining Power, and the Wage Effects of Labor Market Policy," to demonstrate that policies which enhance labor market attachment, provided that they operate through reducing the size and variability of the costs of employment such as child care, should vary in their wage effects based on how much bargaining power workers have. If variable costs of employment are reduced or eliminated, quit rates are lowered, generating additional expected profit but also reducing reservation wages. How much does worker bargaining power affect which party obtains the new surplus? I provide evidence that workers whose expected costs of employment and quit probabilities are reduced by a policy intervention experience little change in their wages on average, but this masks an interaction between the policy and a proxy for worker bargaining power, union concentration. Where union membership is very prevalent, workers are able to reap enough of the resultant surplus that their wages rise, but with little contextual union strength, wages fall.

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And, last and most certainly least, a word from Snoop Dogg/Lion/Dogg: https://www.youtube.com/watch?v=hI8qxPwvaiQ

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Chapter 1

Female Unemployment and Statistical Discrimination: The Revealing Effects of Child Care Subsidies

1.1 Introduction

Starting with papers by Mincer and Jovanovic (1981) and Bartel and Borjas (1981), economists have examined effects of job turnover as reflected in what is known as "mobility." Mobility is essentially the tendency of (generally well-educated) workers to move from job to job rapidly, particularly in the first several years of their careers, in search of the best job. Results show that mobility accelerates wage growth.

I would like to thank Nicholas W. Papageorge, Robert Moffitt, and Richard Spady for providing guidance and feedback. I would also like to acknowledge helpful comments from Michael Darden, Stefanie DeLuca, Susan Dynarski, Christopher Flinn, Kevin Thom, and seminar participants at Davidson College, the U.S. Census Bureau, and the Southern Economic Association (2018). All errors are my own.

However, less investigation has been done regarding another common labor turnover pattern in which less-educated workers in low-wage occupations cycle frequently in and out of employment, rather than moving directly from job to job, a phenomenon which I will call “job churn.” Job churn may arise if a worker has a preference for temporary work arrangements, but could also occur if a worker experiences frequent adverse events which cause them to be unable to work, such as vehicle breakdowns, illnesses, or family emergencies. Observationally, rapid moves between employers and frequent voluntary quits may look like traditional mobility, but in fact they likely contribute to wage stagnation for low-wage workers (Gladden and Taber, 2002). As Stewart (2007) shows, low-wage work and repeat unemployment are tied together, seemingly cyclically. The mobility of young, skilled workers may be a tendency to be encouraged, but the intermittent churning through low-wage jobs of the less educated, marked by frequent unemployment, may call instead for a preventative policy approach.

In this paper, I investigate some of the causes and consequences of job churn and a particular policy that can alter it. I focus on two churn-related patterns: mothers quit their jobs more frequently than other workers, and firms have less permanent employment relationships with female workers than with male workers — that is, they contract women to temporary positions more often and lay them off more readily. I first explore evidence from the Survey of Income and Program Participation (SIPP) that a policy which directly reduces the rate at which working mothers quit their jobs — a child care subsidy — also reduces the rate at which childless women find themselves losing temporary positions or being laid off by their employers.

To understand the latter finding, suppose that firms use gender as a shorthand for attachment to the labor market. High female quit rates driven by working mothers may then lead employers to steer female applicants toward jobs which are themselves inherently less permanent. The SIPP data suggest that the childless women most affected are those who "look like" mothers of young children in terms of their age. Thus, job market attachment generates churn not only directly as a result of household factors like instability in child care needs, but also as a consequence of statistically discriminatory market responses to limited information. The SIPP data also demonstrate that churn has detrimental effects on the careers of workers who experience it, in particular by reducing their access to health insurance, which is often provided by employers only on the condition that an employee has been with the company for a specified length of time.

Given these findings, the job search model I formulate characterizes a potential link between demographic group quit and layoff rates via statistical discrimination. I arrive at this link by modifying the standard search model in three main ways. First, rather than treat quit probabilities simply as worker characteristics impacting the productivity of an employment match, I incorporate these probabilities as governing the frequency of random events that end employment spells, and allow them to vary across individuals and time. Second, I allow jobs on the market to differ in expected natural duration, such as when firms hire seasonal or temporary workers. In the model, this means that some jobs have a higher probability of ending in a layoff in each period than other jobs. Finally, firms do not have full information about applicants when hiring for these positions of varying permanence, knowing only each applicant's gender rather than a full family structure.

In my case, if a subgroup, like single mothers, has a particularly high probability of quitting a job, the model suggests this can result in firms steering all female employees toward shorter-lived jobs. In fact, the model predicts that this steering will have the greatest effect on the layoff rates of women who are not especially likely to quit, as with childless women in the SIPP data. Job churn thus increases for female workers who might otherwise not experience it.

Finally, I reformulate the job search model for estimation and implement it in the data, using the parameter estimates to perform counterfactual exercises. Results suggest that the difference between the absence of child care subsidies altogether and a universal subsidy maximum of \$275 (the largest such value in any state during the relevant period) reduces monthly quit probabilities by 24 percent among less educated mothers (and a great deal more for recipients). Further, this reduction in quit rates leads to spillover benefits for childless women due to the fact that firms fail to differentiate among female workers. The hourly wages of all low-education women increase by around a dollar,[1] while the rate at which they are let go by employers decreases by around 7 percent. Thus, the model suggests that policy spillover effects due to discrimination can be economically significant.

This paper contributes mainly to three strains of economic literature, the first of which concerns statistical discrimination. Discrimination against women based on quit rates can be conceptually linked to discrimination against black men based on rates of criminality, which may perversely be increased by modern movements to "ban the box" (Agan and Starr, 2016; Doleac and Hansen, 2016). Asking female job applicants their expectations with regard to family obligations is effectively a box which has already been banned, which this literature shows may engender statistical discrimination. Fang and Moro (2011) provide a summary of the statistical discrimination literature, which essentially starts with the classic model of Coate and Loury (1993). Moro (2003) formulates a model in which a labor market consisting of complex and simple jobs, a noisy worker productivity signal to firms, and a human capital investment choice lead to depressed wage offers to women. More explicitly focused on quit rates, Sattinger (1998) models the response of hiring firms to the existence of distinguishable groups of workers who differ only in their periodic quit probabilities. However, both papers effectively translate the factor that differentiates male from female workers, the quit probability, into a noisy difference in productivity levels by gender. This

[1]The model does not incorporate any potential effect of subsidies on reservation wage, which would clearly have a significant effect on wage bargaining outcomes in particular. A model which incorporates the direct cost of work in the form of child care expenses is an important potential extension for accurately capturing wage effects, which in the data are in fact insignificant. Bargaining power has a potentially large role to play in this case as well; I address this in another paper.

assumes away any effect from the specific nature of quits as terminations of employment relationships, which my model and results suggest can generate imbalances in the expected durations of jobs actually offered to women with attractive wages.

Furthermore, most of the literature concerning discrimination in the labor market focuses directly on wage differentials; for instance, Gayle and Golan (2012) show that statistical discrimination plays a significant role in the wage gap between men and women, and Bowlus and Grogan (2009) suggest that differing quit rates due to differential responses to family concerns contribute to this gap. Particularly relevant to this paper, Ransom and Oaxaca (2010) find that in a chain of retail stores, monopsony power allows a firm to pay female employees less because the elasticity of their overall quit rates with respect to wages is lower. The model I employ in this paper incorporates variable quit rates directly into the theoretical job search process, which allows for more nuanced effects on wages and job durations. In particular, it suggests that wage effects may not always be apparent where statistical discrimination based on group quit rates is occurring — a result corroborated by the SIPP data in terms of child care policy effects — and that job permanence in terms of layoff rates may also be impacted.

This is a conclusion somewhat similar to that of Barron, Black, and Loewenstein (1993), who show that in a model in which quit rates vary and firms decide how much specific training a worker receives, those with higher quit rates will be sorted by wage offers into jobs that use less capital and will receive less training. Using Employment Opportunity Pilot Project data, the authors suggest that this kind of sorting affects female workers, who get less on-the-job training. This result can be viewed as a response to the question of the gender pay gap, much of which is devoted to examining human capital investment of various kinds. Initially, Mincer (1974) identify women's plans to leave the labor force (particularly for parenthood) as a reason they themselves would invest less in their own human capital. However, Gronau (1988) shows that the causality may well run the other way — firms, anticipating that some women are liable to quit their jobs, are reluctant to place them in positions which require extensive investment in skill improvement over time. For Gronau, this contributes to poorer wage outcomes for women, who then have less incentive than men to stay in the labor force upon having children and thus depart, confirming firms' expectations. In this paper, I examine another aspect of this dynamic: when female workers persist in seeking work whether or not they have children, how are they impacted in the range of jobs offered to them? It is not only their wages which are depressed, but also the expected duration of employment at any given job. And if employers are reluctant to place women *in positions* that require long-term investment and thus let them go more frequently, can policy alleviate this?

This paper thus also contributes to the literature directly examining the effects of child care subsidy policy. Blau (2003) provides a thorough review of both the structure of child care subsidy programs and the economic literature concerning its effects. He finds that estimated elasticities of labor supply with respect to the price of child care (intended as a stand-in for the effect of a subsidy) vary widely, but are smaller when the decision to use paid care is accounted for separately from the labor supply decision. Subsequent research by Tekin (2007) and Blau and Tekin (2007) suggests that child care subsidies do in fact bolster employment rates among mothers, even accounting for the decision to take up the subsidy, with the former paper suggesting a 13 percentage point increase in employment rates among recipients. But the mechanisms behind this elasticity remain clouded. Do subsidies simply push some parents across a binary labor supply threshold? Or is there also some volatility in other child care options — family, school, etc. — to which parents resort while working which might cause them to work only intermittently in the absence of funding for formal child care? As evidence of a policy effect similar to the latter scenario, Graves (2013) examines the effect of a move to year-round schooling with breaks every three weeks on the labor supply of mothers of school-age children in the school district. She finds a negative response, suggesting that some mothers were reliant on the steady child care schools provided during the traditional school year in order to work. In this paper I build on these results by providing evidence that subsidies for formal child care alleviate the volatility of child care arrangements for parents at low-wage jobs, while also acknowledging that the effects of child care subsidies may include spill-over to non-recipient female workers.

A paper closely related to this paper and both of the above literatures is that by Lin and Tanaka (2016). The authors look into the effects of child care availability on the hiring of young women in Japan, utilizing a signalling model in which workers can select different job training tracks that lend themselves to short- or long-term jobs. The authors find evidence of statistical discrimination using regional child care availability and group averages of labor force attachment as well as survey answers about individual quit intentions. However, in order to generate a separating equilibrium their model relies on the ability of workers to propose delayed-payment contracts, which in the U.S. low-wage context are not likely to be viable. The results presented by Lin and Tanaka (2016) focus on the effects of switching between separating and pooling equilibria on total hiring and typical wages, while the full search model implemented in this paper permits exploration of further effects such as individual job duration and sorting.[2]

Finally, the theoretical model in this paper links it to the literature developing models of labor search, with its roots in Mortensen (1977) and Burdett (1978). Search models which generate worker quits typically do so via on-the-job search resembling the "mobility" discussed above, by which an employee may leave one firm for another, better-paying one within an employment spell; this approach is also generally taken with a macro perspective

[2]Lin and Tanaka (2016) use a calibrated version of their model to conclude that child care subsidies are detrimental even for potential recipients because, in order to maintain the separating equilibrium as subsidies make it easier for mothers to work, firms must enforce greater and greater payment delays on women who are not likely to leave. Only once a pooling equilibrium is reached do subsidies benefit workers. Labor markets in which ensuring these kinds of delayed payments is difficult for firms might reasonably be expected to show the latter effect.

toward overall quit rates (Pissarides, 1994; Gautier, Teulings, and Vuuren, 2010), rather than an interest in the impact of quits on individuals' labor market trajectories. As noted, however, in the low-wage markets in which U.S. child care policy has its largest effect, this kind of job churn is not the most common sort. Neither, intuitively, are job-to-job moves the kinds of quits that child care subsidies avert most effectively. The model in this paper contributes by allowing for variability in the probability a worker will quit due to the value of non-employment, as broadly suggested by Flinn and Heckman (1982), as well as effects of this variability on outcomes in the Nash bargaining framework examined closely by Flinn (2003).

The remainder of the paper proceeds as follows. I describe the SIPP data used in this paper in Section 3.3, and in Section 3.4 provide evidence therefrom of the detrimental effects of inconsistent employment histories, as well as the nuanced effects of child care subsidies on the job churn rates of women. In Section 3.2 I provide a theoretical model of job search which has the ability to characterize the salient patterns. I estimate a version of the model, noting identification issues, and report the results in Section 1.4. In Section 1.4.3 I complete the counterfactual exercises. Section 3.5 concludes.

1.2 Data

In this section I describe the data set used in this paper, as well as the construction of key variables and summary statistics. I then provide linear regression and hazard rate model analysis establishing the patterns for which the model in Section 3.2 accounts.

1.2.1 Survey of Income and Program Participation

I employ data from the 2001 and 2004 panels of the Survey of Income and Program Participation (SIPP). I restrict the working sample to individuals who at all points in the sample are between the ages of 25 and 55 in order to reduce the impact of retirement on the older end and of individuals who alternate between temporary work and school on the younger end. Individuals who report significant self-employment income in any period are removed as well,[3] along with individuals who ever fail to provide interview responses in a particular wave.[4]

SIPP respondents are surveyed in four monthly rotations, each rotation representing approximately one quarter of the sample. During a "wave," respondents provide answers to each survey question for each of the previous four months.[5] In practice, interviewees frequently give the same answer for all four months in question at each survey, so that there is a tendency for changes in activity patterns — such as employment spells — to be clustered at the interview month, an issue known as "seam bias." This likely decreases the measurable presence of employment status transitions because brief transitional periods which occur between interviews may be lost. In fact, a majority of individuals in the sample who quit their jobs for personal reasons (specifically *not* for another job) or are fired have a job immediately in the following month of data. Intuitively, this would suggest that my results with regard to the impact of policy on churn are conservative, because repeated

[3]Employment statuses are inconsistently reported in the SIPP alongside self-generated income. This creates an issue for recording and measuring employment spell durations. Removing such individuals results in a reduction of the sample size of less than 5 percent.

[4]Non-interview waves in the SIPP are filled in with imputed data, which generates a relatively large number potentially spurious employment status transitions. Eliminating these respondents reduces the sample size by 13 percent.

[5]More specifically, if the panel begins in January, rotation 1 is interviewed in January and answers questions concerning employment status, public assistance usage, etc. for October, November, December, and January, or "wave 1." The respondents in rotation 1 are not interviewed again until May, in which they provide information for the intervening months constituting wave 2. Rotation 2 starts similarly in February by providing answers back to November, and the full sample is has supplied its wave 1 responses by the end of April.

brief stints in unemployment are more common among the low-wage workers for whom child care policy is most relevant. On the other hand, if child care subsidies do not eliminate unemployment spells but merely make them short enough to disappear between waves, the bias would run in the opposite direction. At first glance, it seems reasonable to guess that the former source of bias would be greater.

There are multiple ways to handle seam bias; for instance, much of the SIPP literature focuses on the last month in each wave as the only possible transition point. Ham, Li, and Shore-Sheppard (2016) devise a method for estimating the likelihood that an end-of-wave transition actually occurred during the other months in the wave, and analyze the effects of welfare policies on employment status spell durations. I attempt to alleviate the seam bias issue by instead using the work start and end dates available in the SIPP data. It is possible to adjust or impute many employment records to correct for some of the missing transitions. Since my concern is not durations per se but rather the incidence of events like quits and layoffs, capturing as many actual transitions as possible is the main goal of this correction.

1.2.2 Key Variables

In this section I define the most important variables in my analysis — job churn rates, different types of job separation events and churn, and occupational groupings — and provide a discussion of the focal policy variable, child care subsidy values.

Job Churn and Subtypes. The outcome variable I use most frequently is what I will call a respondent's "churn rate." The base rate of churn for an individual in a given period (month) is essentially the percent of preceding periods in which the individual experienced a job separation — that is, a transition from employed status to nonemployed status. Such events are tabulated as they occur in the survey; work histories in the SIPP are insufficient to examine individuals' employment volatility prior to their appearance in the data. Formally, the churn rate is equal to:

$$100 \times \frac{\sum_{\tau=1}^{t} s_{i\tau}}{t},$$

where t is the current in-panel period and the $s_{i\tau}$ are periodic indicators of whether a job separation event occurred in the given month τ. This expression is similar to the construction of the measure of job mobility used by Munasinghe and Sigman (2004). An increase of one unit in this measure represents a one percentage point increase in the monthly job separation "rate" of a worker.[6] Because these rates are the objects of interest, the high frequency with which SIPP responses are gathered is one significant advantage of this data set.

Another key feature is the SIPP question concerning the cause of respondents' departures from employers. Respondents have fifteen options, but these can be categorized in more parsimonious ways. The categories I use admit four general types of events:

- ↪ Firing churn: firings for cause
- ↪ Layoff churn: layoffs, employer closure or sale, and the ends of temporary work arrangements
- ↪ Match Quit churn: quits due to working conditions and departures for a new job
- ↪ Life Quit churn: illnesses and injuries, departures for familial obligations or school or retirement[7], and voluntary quits for "other" reasons, which can be shown to be correlated with familial events like the birth of children

Below, I occasionally refer to the first two types as "demand-side" events or churn, and the last two as "supply-side." In addition, over 40 percent of transitions from employed to

[6]Because this calculation could result in large jumps in the rate during the first few months of a respondent's time in the panel, I run the basic churn rate regressions described in this section on a subsample excluding the first wave (four months) for each individual. This does not alter the patterns captured in the results.

[7]Retirement and departures for school are quite rare due to age restrictions placed on the sample.

not-employed in the data are not accompanied by information regarding the cause of the transition. These events are collected under the category "Unknown." The contributions of this category to overall employment status churn are somewhat erratic, but the category is occasionally included for completeness. Rates of these different types of churn are calculated similarly to the overall rate.

Occupational Groups. Finally, I control for occupation throughout this paper using a simplified structure which includes four job categories constructed so that the educational requirements and wage outcomes of their constituent occupations, as evidenced by the SIPP data, are relatively similar: high-end, mid-tier, and low-end services, and manual work. High-end services include management, STEM occupations, and sales of financial services and large durables like homes and vehicles (i.e., non-retail items). Mid-tier services covers personal and health services and clerical work. Low-end services include hospitality, food service, and retail, while manual occupations include trades like construction and manufacturing as well as mechanics and transportation. Their basic purpose is the reduction of the state space for structural estimation. However, when I use them in place of much more detailed occupational categories (a set of 18 dummies based on occupational codes provided by the SIPP) in the regressions I perform below, these parsimonious groupings suffice to control for any relevant occupational effects and reverting to the larger set of controls does not alter my results.

Child Care Subsidies

The key policy variable in this paper is the child care subsidy. In the U.S., public child care assistance is provided by the states using block grant funds under the federal Child Care and Development Fund (CCDF). Created in 1996 by the Personal Responsibility and Work Opportunity Reconciliation Act (PRWORA), the CCDF represented the consolidation of multiple disparate child care assistance programs into funding block granted to states with relatively loose restrictions on the rules states employ in disbursing the funds. For instance, the federal maximum eligibility threshold for a child care subsidy is 85 percent of state median income, but most states set the threshold lower, with states providing subsidies only to parents making less than 50 percent of state median income in about one-fifth of state-year observations between 2000 and 2007. States also have a great deal of flexibility regarding any fees as well as the maximum available size of the subsidy, which is the feature of state subsidy policy on which I focus in this paper.

It is worth noting that, shortly after the CCDF was created, it was estimated that child care subsidies covered approximately 12-15 percent of the children who were in fact eligible for care (Administration for Children and Families, 2000). In the SIPP data, I construct an eligibility indicator using state eligibility criteria, the relevant state median income, and individuals' household income and parental status. Respondents disclose whether they have received government subsidies for child care in each month of the panel. In comparing the latter to the former, I too find that around 12 percent of eligible female workers receive subsidies. However, this is not solely, or even mostly, an issue of takeup — many states maintained waitlists for families who are eligible and have applied for child care subsidies but cannot be funded under the CCDF grant budgets.

This fact prompts the question: what generates differences in subsidy policy both across states and within states over time? Could variations in the block grant value available to each state be driving these differences? As I employ models both with and without state fixed effects below, both kinds of variation are of interest. The legislation which created the CCDF, the Child Care and Development Block Grant Act, stipulates[8] that each state receive a grant amount based on the following calculation:

[8] United States Congress (1990)

1. Calculate the fraction of all U.S. children under 5 years of age residing in the state;
2. Calculate the fraction of all U.S. schoolchildren receiving free or reduced-price lunch attending school in the state;
3. Take the average of the above two values;
4. Multiply this average by the ratio of state per capita income to U.S. per capita income;
5. Supply the resulting percentage of the federal block grant value to the state.

Thus, barring dramatic changes in the young or reduced-price lunch populations across states or in incomes in the state relative to the rest of the country, grant values to different states and ratios across states ought to be relatively consistent over time, and are intended to reflect the anticipated need for child care subsidies in each state. Moreover, the total block grant amount supplied by the federal government remained at $5 billion in 2006, an amount identical to that appropriated for the CCDF at its inception. Variations in subsidy features, including weekly maxima, across states and within states over time are thus likely to be the result of political changes at the state level rather than a response to funding changes. Throughout this paper, I assume that whatever generates this variation, it is exogenous to the economic outcomes of state residents conditional on year (and, in the regression case, state) fixed effects, controls for other state-level labor market policies such as minimum wages, occupation controls, and demographics.

For simplicity, I use the maximum subsidy payout per week to reflect each state's generosity with regard to subsidies.[9] I extract child care assistance payment maxima for state-year pairs from biannual reports produced by the National Child Care Information Center of state plans for their use of Child Care and Development Fund dollars. Because these

[9] Variables reflecting individuals' eligibility as well as state-level income limits on eligibility were included in the estimation of many of the models in Section 3.4, but were generally estimated to have little effect on churn and are thus excluded from the analysis here.

plans were submitted biannually, states' child care subsidy maxima are set at constant values for two-year periods. Figure 9 shows the trajectories of child care subsidy policy by state over the eight-year course of the two SIPP panels. It demonstrates that there is meaningful variation in maximum subsidy levels both among states in each year and within many states over time.[10] For use in reduced-form estimation, I standardize the subsidy maximum variable so that coefficients represent the effect of a one-standard-deviation increase in the maximum subsidy value. Three other policy variables are retained in the set of regressors in Section 3.4: a state minimum wage variable, a variable recording the contemporaneous state maximum on weekly unemployment insurance (UI) payouts to out-of-work individuals, and one reflecting the generosity of workers' compensation in the given state and year. These are intended to reflect the labor market policy environment prevailing in each state in each year. In the churn rate regressions, I also incorporate state-of-residence dummies.[11]

1.2.3 Summary Statistics

Summary statistics for the working sample are found in Table 1, which shows means of many basic control variables for the full analytic sample of individuals as well as some important subgroups. Those with lower educational attainment are less likely to be married, but have more children in addition to displaying higher overall churn rates. Women are seldom in the layoff-prone manual occupations, but are still laid off at similar rates to men.

Overall, easily the most common types of churn are layoffs and quits due to circumstances beyond the employment relationship. Groups that display greater overall job churn tend to be less educated, and to experience more "exterior" events like layoffs and family

[10] In results not included in this paper, I reestimate the most basic models in Section 3.4 with each state in turn removed from the sample to ensure no single state dictated the size and significance of the estimates. Results are similar in every round.

[11] When I apply duration models below, I instead use four regional dummies. The 48 state indicators — a handful of small states are grouped together in the data — present too large a parameter set for the binary-outcome hazard rate specification.

issues. There are many features of this sort of churn that distinguish it from that experienced by the more-educated — the types of separation events and modal occupations of those who are "upwardly mobile" are quite different from those of workers who "churn." One pattern not apparent in Table 1 is the fact that while their overall rates of churn are lower, workers in more advantaged groups, like those with greater education, report significantly more departures for new jobs: over 16 percent of all recorded job separation events and 8 percent of transit-to-nonemployment events among the college educated are departures for a specific new job, while these percentages are under 10 and 5 for those with only a high school diploma, and the college educated are also more likely to leave a job without entering a recorded nonemployment spell. Educated individuals thus appear to engage in more on-the-job search and job-to-job transitions, even when this results in (generally short) periods of unemployment.

Table 2 reports statistics as of exit from the panel by number of employment separation events recorded. As in-panel separations increase, subsamples become less white, less frequently married, less educated (although some-college attainers are over-represented at high churn counts), younger, somewhat more likely to work in manual occupations, and nearly twice as likely to work in the low-end services. Departures from employment for familial reasons are relatively common amongst those with just one separation event, but don't recur at the same rate as other types of separation amongst those with multiple such events. This reflects their greater tendency to be permanent or semi-permanent changes in labor supply at significant family events like births.

Low-wage service occupations like retail sales and hospitality generate high levels of job churn as demonstrated by Table 2, but also contain a high concentration of workers of the type most likely to access child care subsidies. Female workers with a high school diploma or less appear frequently in the mid-tier and low-end services, with these occupational groups totaling over 60 percent of this subsample of the labor force. That churn and low wages are strongly associated among working women suggests that churn is not a particularly advantageous pattern for them, but indicates a potentially strong role for labor market attachment policy aimed at this group, such as child care subsidization.

1.2.4 Preliminary Data Analysis

In this section, I establish key findings from the SIPP data bearing on the relationships among child care subsidies, quit rates, layoff rates, and gender. For each set of estimates, I use all person-month observations in the working sample. For this reason, I cluster standard errors at the individual level.[12]

The findings include: (1) job churn has a negative effect on worker outcomes; (2) women with identical measurable productivity characteristics are laid off more readily than men; (3) more generous child care subsidy policies are related to a reduction in these higher layoff frequencies among childless women as well as reduced rates of voluntary quits by both mothers and (to a lesser degree) childless women; (4) the reduction in layoffs does not appear to be related to large shifts in the composition of the labor force and is strongest among the subgroups predicted by the statistical discrimination model, namely young women without children; and (5) the reduction in mothers' quits is the result of actual subsidy receipt.

Job churn has negative consequences. It is important to differentiate between churn and traditional job mobility because the former has detrimental effects which it might be desirable to limit with policy. Table 3 demonstrates that job churn generated by either demand- or supply-side separation events is associated with poor results for workers across an array of outcomes. In particular, estimates from OLS regressions reported in the first and second panels show deleterious associations between churn rates and subsequent wage levels, access to health insurance while employed, health, food adequacy, home ownership,

[12]The basic results are robust to the alternative use of an individual random effects model.

home values given ownership, and welfare recipiency. Because there are concerns about endogeneity with regard to each of these outcomes, I use state-year child care subsidy policy (along with worker's comp generosity) as instruments for overall churn rates to produce the results in the third panel. Sample sizes sufficient for this exercise only exist with respect to wages and health coverage, since the other outcome variables are based on responses to SIPP topical modules, asked only in specific waves during the panel. F-test values imply that, for these outcomes, these policy structures are decent instruments for churn. Churn rates have a statistically significant negative effect on subsequent wages and, even given employment, health insurance coverage. This makes sense, since most employer-provided health insurance comes with requirements as to the length of the employment relationship, and workers with high churn rates will often just be starting new jobs.

Women experience layoffs at a higher rate. Churn rate regression results (Table 4)[13] suggest that women of the same race, age, education, occupation, marital and disability status, and state or region are more likely to experience layoffs than men. This effect seems to be largest for the least educated. Note that controlling for occupation is important, because layoffs are an integral part of working in the trades occupations, which are overwhelmingly male. Raw rates of layoff are a bit higher amongst men for this reason. However, the main concern here is not so much overall layoff rates as it is whether any given employer will be more likely to lay off, or place in temporary positions, a particular kind of worker.[14] This

[13]In results available on request, I replicate these results using a duration model, with the layoff hazard rate the object of interest. Duration or hazard models treat spells of employment or nonemployment as units in which in each period there is some probability or "hazard rate" of experiencing the end of that spell, and constituent hazard rates of experiencing specific spell-ending events like firings, layoffs, or quits. The effects of covariates, including spell duration itself, on these hazards can be estimated under certain conditions and assumptions. The foundations of the duration model approach and its connection with structural models of employment decisions like that specified in Section 3.2 are developed by Flinn and Heckman (1982), and van den Berg (2001) provides a thorough summary of the theory and usage of duration models.

[14]In addition, Fujita and Moscarini (2017) demonstrate that recall from unemployment to the employer by whom a worker was laid off is common, and has a significant influence on rates of separation and movement to new jobs. Recall is particularly prevalent in the manual occupations, indicating that male workers' experience of "layoffs" or temporary work is likely different from that of female workers in other occupations. Men in

within-firm process is where statistical discrimination becomes relevant and quit probabilities, and thereby child care policy, can have a spillover effect on other forms of job churn. Next, I demonstrate that the data reflect just such a spillover.

Child care policy reduces multiple types of job separation rates. Table 5 demonstrates that child care subsidy rates reduce the overall rate of job separation, and that the majority of this effect can be attributed to a corresponding reduction in supply-side separation events, which is precisely what would be expected — child care subsidies reduce the need for parents to adjust their labor supply in response to child care issues. It is easy to explain the reduction in match-related quits, because a large proportion of these are voluntary quits due to "unsatisfactory work arrangements," in particular hours. The second panel of Table 5[15] reveals that, among those with children, this specific kind of churn reduction is strongest for women as well as those who work in the low-end service occupations, restaurant service, hospitality, and retail. In these occupations, while part-time hours are common, so are inconsistent but inflexible scheduling schemes. An employee who can handle this absent family issues may find it difficult to adjust adequately when an inconsistent or impermanent child care arrangement, like a family member or an after-school program, falls through or ends. A worker who quits in this environment may claim to have done so due to an unsatisfactory work arrangement. The rate of job separations due to personal concerns drops as well, though the estimated decrease is more imprecisely estimated and is not statistically significant at conventional levels (p-value=.22). Overall, though, increased child care subsidy maxima are estimated to significantly reduce quits, particularly for the expected demographic groups, mothers in low-wage work.

nonemployment spells likely experience reemployment more rapidly and are more likely to maintain the employment relationships key to health coverage and wage growth as discussed previously.

[15] In the lower panels of the table, I have run the same churn rate regression for subsamples by gender, occupation, and education, but have included only the significant results for the coefficient on child care subsidies in the table.

The third panel of Table 5 displays the effects of increased child care subsidy maxima on job separation rates among respondents who in the given month have no children in their households, in the full sample as well as in a subsample including only those with no more than a high school education. The overall churn-reducing effect of the child care subsidy maximum is around three-quarters the size of the similarly-estimated effect among parents and is nearly statistically significant (p-value=.16).[16] This is curious, since intuitively a subsidy ought not have any effect on those who cannot access it. Moreover, as the table breaks the effect down by demographic and other characteristics, it reveals a relatively dramatic, statistically significant drop in layoffs amongst low-educated workers and those in the low-end service occupations. In particular, female workers drive this result. Therefore, workers with similar characteristics to those whose quit rates are reduced by policy, namely women in low-income (and thus subsidy-qualifying) jobs who resemble mothers of young children, experience a reduction in demand-side separations.

What might explain such a result?

Statistical discrimination is a reasonable explanation for layoff rate reductions. There are a few reasons why a relationship between child care policy and the labor market experience of childless women might appear in estimation. The first and simplest is that child care subsidization is correlated with some omitted variable also associated with layoffs. In churn rate regressions, I include state and year dummies and other policy variables (unemployment insurance maxima, minimum wages, and worker's compensation generosity) characterizing the general "political stance" toward labor in each state in an attempt to mitigate this potential issue. One other concern is that child care subsidy policy may affect the *composition* of female labor supply so significantly that childless women are pushed into

[16]The analogous estimated effect in a duration model is negative and statistically significant, though the exclusion of state dummies from this specification generates concerns for validity — particularly in the case of layoffs, where this effect is concentrated, because the occupational distribution among states is strongly related to layoff rates and may be correlated with policy. Duration model results are thus not reported here.

new positions or out of the labor force entirely, which could of course result in fewer layoffs. I make a few adjustments to the specification to dispel this concern. In the last panel of Table 5, all individuals who never work at any time during their participation in the survey are removed from the estimation sample. The clearly similar results demonstrate that the effect is not due to childless women who are pushed out of the labor force by the beginning of the second SIPP cohort by policy enacted during the first, or by policy differences across states.

If labor force composition effects are not to be credited with the reduction in layoffs among childless women, statistical discrimination seems like a good candidate. One way to assess its feasibility is to further divide the sample of low-education women into those who “look most like” mothers with greater volatility in their home lives and thus higher quit rates. One characteristic this suggests most strongly is relative youth — firms, knowing nothing other than gender and age, might reasonably be less likely to view women beyond the ages at which mothers are typically caring for young children as frequent quitters with unstable home lives. I therefore split the less-educated female sample at the age of 40 (that is, any individual who is never older than 40 in the sample is below the cutoff) in order to assess the differences in subsidy effects by age, with particular attention to layoffs among the childless.

Table 6 shows that among low-educated women — the group in which the effect is concentrated — the layoff reduction effect of child care subsidization is in fact much larger for women under 40, and is insignificant among those who ever reach 40 or beyond in-sample. Thus, there is suggestive evidence that the oldest women in the sample reap less benefit in the way of layoff reduction than do women at ages which employers might more frequently associate with the presence of young children. This finding bolsters the case that changing the quit rates of young mothers alters a landscape of statistical discrimination against other young women.

Subsidy receipt drives the reduction in mothers' quits. It is not necessarily clear from the above results, which do not focus on actual subsidy receipt, that the estimated supply-side effects are due to altered labor market behavior on the part of those workers who actually receive subsidies. The specifications utilized above permit examination of effects on other workers, but do not necessarily establish a link between the policy itself and the measured outcomes. To remedy this in the case of recipients, I include in the specification reported in Table 7 a dummy indicating receipt of a subsidy for child care during the panel, and interact it with the state subsidy maximum value. Receipt is of course endogenous, but the question being asked here is merely whether the estimated effect of increases in the value of subsidies on labor supply can reasonably be credited to the actual disbursement of subsidies. The results in Table 7 suggest that this is so. The meaningful reduction in quits for family reasons when subsidies are larger is entirely due to a large and statistically significant reduction in such quits among those who report receiving a subsidy during the panel. The reduction in unsatisfied quits is also of much greater magnitude for subsidy recipients. This is unsurprisingly especially true for mothers.[17] These findings strongly suggest that, whatever is the process that determines whether a parent applies for and receives a subsidy, subsidy receipt is directly linked to reductions in mothers' quit rates.

In Section 3.2 I will demonstrate that a model of statistical discrimination predicts that quits among childless women could also be reduced by generous child care subsidies as a consequence of improved wage outcomes for all women, so the finding of a statistically significant reduction in match-related quits for subsidy non-recipients is no surprise. Finally, the fact that subsidy receipt is so clearly linked to the reduction in quits among mothers

[17]One related concern may be that it is not volatility associated with raising young children generating these separations, but birth events. In results available on request, I include interactions of subsidy maxima with an indicator for an in-spell birth and the age of the youngest child in the household and its square. The first specification shows no significant effect unique to mothers who give birth during an employment spell — which is unsurprising, given that the cost of child care may not be the most important factor dictating the departure of a new parent from a job. The second specification suggests that the quit-reducing effects of child care subsidies max out at a child age of around six years, rather than in infancy.

might favorably be interpreted as evidence that the other significant effects found in the presence of more generous child care subsidies — specifically reductions in layoffs — could be credited to the impact of such policy as well.

1.3 Model

In this section, I formulate a model of job search and matching which accounts explicitly for the impact of demographic group quit rates on various outcomes. The agents in the model are workers who, when not employed, search for jobs with two characteristics: a probability that in each period the job will end in a layoff, and a wage offer bargained based on the productivity of the job and the applicant (and other parameters).

Job search models provide a straightforward way to examine how labor market outcomes depend on quit probabilities, since the latter enter workers' and firms' valuation of employment relationships directly as the probability that those relationships will be terminated, an outcome both parties want to avoid. Moreover, the model nests a wage bargaining structure in which wages can be allowed to respond to quit and layoff rates jointly, linking the two outcomes; as I explain in this section, firms with layoff-prone jobs will care less about applicants' propensity to quit, and therefore not punish potential quitters in wage negotiations as much as firms with high-duration job openings. High-turnover jobs thus attract high-turnover workers, and vice versa. Since this is a story about the matching of a particular kind of employer to a particular kind of employee, a search and matching model is well-suited to the task of assessing it.

In order to explain the empirical patterns in Section 3.4 as a consequence of statistical discrimination, I make three important adjustments to the essential search and matching framework. First, I incorporate individually variable quit probabilities in the model. The probability of a costly quit ending an employment relationship is allowed to vary by demographic characteristics including gender and the presence of children as well as the wage, and this probability impacts how workers and firms value employment contracts because it represents the threat that the contracts will end. This stands in contrast to a typical model of statistical discrimination on quit rates, in which a higher quit probability reduces the productivity of a match.

Second, I allow jobs on the market to differ in their natural periodic layoff probability, denoted ϕ. As noted above, firms will adjust their wage offers based on quit probabilities, which will have the effect of pushing workers likely to quit towards jobs likely to end quickly in a layoff anyway. Workers perceived as quit-prone will thus experience more frequent layoffs, as in the results in Section 3.4.

Finally, I assume that firms cannot know a given worker's true quit probability at the time of a job match. Specifically, firms can see workers' gender, but not their familial structure. They therefore project quit probabilities based on this limited knowledge. This, plus the fact that quits negatively impact firms' bottom lines, leads to statistical discrimination in the hiring process against those in the gender group — women — that includes the most quit-prone workers — mothers of young children.

In combination, these features of the model allow changes in mothers' quit probabilities to influence the layoff-proneness of the jobs to which wage offers push all female workers. In fact, as I discuss in Section 1.3.2, the model predicts that the change in layoff *rates*, like those measured as outcomes in Section 3.4, will be most significant for those women who are unlikely to quit before a layoff occurs — specifically childless women, as in the foregoing empirical results. The model specified in this section thus serves to theoretically examine the findings in Section 3.4, as well as to lay the foundation for a slightly simplified version to be estimated in Section 1.4.

1.3.1 Search Model Specification

The model is based on the classic search and matching framework[18] in which potential workers in the nonemployed state are matched with employers in continuous time at a given rate, denoted λ^{θ}. Once a match occurs, a match-specific productivity level θ is revealed. The match wage offer is determined via a Nash bargaining process in which the bargaining power parameter α determines how much of the match surplus, the difference between θ and the worker's reservation wage, is recovered by the worker. Given this offer, the worker decides whether to accept and enter the employed state or to remain in the nonemployed state and continue searching. In the canonical model, there is usually a constant rate of exit from employment called the "job destruction rate," here ϕ, which I will instead call the "layoff probability." It is at this rate that employees exogenously return to the nonemployed state. There is no on-the-job search.

Let the distribution of θ be denoted $G(\theta)$, and for the time being assume that this distribution is the same across worker subgroups $j \in J$. A worker's subgroup j is invisible to the firm, though they are nested by gender, which is known. In the employment state, individual i pays a flow utility cost c_{it}. New employment disutility levels are drawn at frequency λ^{c} from a distribution $F_j(c)$ which depends on the group identity of the individual and has support $C = [\underline{c}, \infty)$, and the cost remains at the drawn value until a new draw is taken. Fluctuations in c_{it} explain quit behavior because if a high employment cost value is drawn, the present discounted value (PDV) of employment to the worker decreases, and may decrease enough to alter the worker's decision with regard to their current employment arrangement.[19]

[18] A thorough exploration of the basic search model can be found in Chapter 3 of Flinn (2010).

[19] Bontemps, Robin, and den Berg (1999) allow for a distribution of opportunity cost across workers, but not within-individual changes. On the other hand, Bowlus and Grogan (2009) formulate a model with a gender-specific rate of at-home events which cause quits, but do not link this with other types of job separation or to policy variables within the model or differentiate among subgroups, which I do so as to examine statistical discrimination specifically.

When a new draw of c_{it} induces a quit by a worker or an exogenous demand-side separation occurs (at rate ϕ), firms pay a cost c^q_ϕ. The subscript ϕ indicates an allowance for differences in separation costs across jobs based on the expected duration of the job (the inverse of the job-specific exogenous layoff rate). In the model, separation costs are supposed to be larger for long-lived (small-ϕ) jobs like management and professional positions than for short-lived positions like those on the front-lines of the low-wage service industries. This assumption is strongly supported by the range of cost values found in the management literature, as well as intuition. Large retail and hospitality employers maintain a constant pool of applicants to entry-level jobs, perform relatively little vetting in the hiring process, and in fact often outsource the process entirely to temporary employment agencies. As will become clear in the estimation exposition in Section 1.4.1, this is an important channel via which quit and layoff rates become associated: because firms with short-lived jobs incur much smaller costs when workers separate from them, they care less about the prospect that a worker will quit. This means they differentiate their wage offers less in response to perceived applicant quit rates.

While it is intuitively clear that these costs exist and follow such a pattern, estimates of how substantial they are have been mostly the domain of management literature, particularly that dealing with the health care industry, and reliant on surveys of front-line managers.[20] In Section 1.4, I estimate the cost of separations to firms based on differences in wage offers accepted by workers with different expected quit rates, holding other characteristics constant. Since firm separation costs are not the focus of this paper, this estimation method is allowed to be somewhat crude, but the estimated values are well within the general range of estimates described in the management literature.

As I demonstrate in this section, the intensity of firms' incentive to alter wage offers

[20] See Waldman et al. (2004); Hinkin and Tracey (2000); Davidson, Timo, and Wang (2010); McKinney, Bartlett, and Mulvaney (2007) for estimates of separation costs in the hospitality and medical industries ranging from around $2,000 to tens of thousands of dollars, depending on occupation.

in the face of the potential cost of a quit will depend in part on the expected duration of the job as captured by the demand-side termination rate, not only because of the costs that differ due to the above assumption, but also because firms with short-term jobs expect to pay separation costs with a high frequency regardless of quit rates. The job-specific rate of demand-side separation, ϕ, is drawn from an exogenously given distribution $H(\phi)$ at the time of a labor market match, and is known to both the firm and the individual. It may be helpful to think of firms as having vacancies at many points on $H(\phi)$ and formulating hiring rules based on the layoff rate imposed on each job, in which case some workers may be favored for long-lasting positions over others based on relevant characteristics. I assume that while the distributions G, H, and F_j are known to all parties, c_{it} and j (beyond gender) are private information not communicable to firms.

Worker State Valuations. After rearranging terms in a Bellman equation expression, the value of the nonemployment state can be expressed as

$$V_j^N(c_{it}) = \left(\rho + \lambda^\theta + \lambda^c\right)^{-1} \times$$
$$\left(\lambda^\theta \int_\Theta \int_\Phi \max\left[V_j^E(\theta, \phi, c_{it}), V_j^N(c_{it})\right] dH(\phi)\, dG(\theta) + \lambda^c \int_{\underline{c}}^{\infty} V_j^N(c)\, dF_j(c)\right), \quad (1.1)$$

where Θ is the support of θ, Φ is the support of ϕ, and individuals and firms discount the future at shared rate $(1+\rho)^{-1}$. Thus, the unemployed searcher's value is generated by the sum of the expected payoff from a job match across the distributions of θ and ϕ and the expected change in the value of the nonemployment state given a new draw of c. New disutility draws alter V_j^N because they affect the expected value of any future job matches. Because c constitutes a flow disutility of the employment state, a flow utility of the nonemployment state would not be separately identifiable and is omitted.

If the flow utility of employment at a particular match is equal to the wage $w_j(\theta, \phi)$ upon which a firm will agree with a group-j applicant via Nash bargaining given θ and ϕ, then the value of the employment state can be similarly expressed as

$$V_j^E(\theta, \phi, c_{it}) = \left(\rho + \phi + \lambda_j^c\right)^{-1} \times$$

$$\left(w_j(\theta, \phi) - c_{it} + \lambda^c \left[\int_{-\underline{c}}^{c^*} V_j^E(\theta, \phi, c)\, dF_j(c) + \int_{c^*}^{\infty} V_j^N(c)\, dF_j(c)\right]\right), \quad (1.2)$$

where $c^*(\theta, \phi; j)$ is a "critical disutility value" generated by the prescribed wage-layoff rate pair, specifically that cost draw value above which the worker will quit a job at that wage and return to the nonemployment state. While employed, the worker earns the wage w_j and pays the cost of employment c_{it}, but also anticipates new draws from F_j which will either alter the continuation value of the employed state if below c^* or cause a return to V_j^N if above.

Firm Valuation of Employment Relationship. The next piece of the model is an expression of the firm's value of an employment relationship. Define for each group j a function $F_j^*(\theta, \phi)$ to be equal to the cumulative distribution function (CDF) value of $c^*(\theta, \phi; j)$ on F_j — the proportion of the possible cost draws at which the worker will take or stay at such a job. Then $\left(1 - F_j^*(\theta, \phi)\right)$ is the probability that any given employment disutility draw will result in a worker in group j quitting the job defined by (θ, ϕ). The value of a group j worker to a firm in a match defined by (θ, ϕ) is therefore:

$$V_\phi^F(\theta, w, j) = \left(\rho + \phi + \lambda^c\left(1 - F_j^*(\theta, \phi)\right)\right)^{-1}\left(\theta - w_j(\theta, \phi) - \lambda^c\left(1 - F_j^*(\theta, \phi) + \phi\right) c^q\right). \quad (1.3)$$

Wages Under Incomplete Information: Statistical Discrimination. In a typical search specification, job applicants' valuation of the employment state given the wage level is known to all parties. In this case, however, this valuation depends on a random variable c_{it} and its distribution, known only to the applicant. Applicants can bargain based only on the features of their valuations of employment and nonemployment known to firms, which with respect to c_{it} is only gender. Thus, in bargaining, firms negotiate only against the expected value of employment and nonemployment to a worker of known gender, and select a wage based on (θ, ϕ) so that the mean individual expected to *accept* that offer would in fact negotiate to that wage. If an upper bar indicates an expected value from the firm's perspective (and abusing notation by continuing with j subscripts though firms only see the broader gender groups), the Nash bargaining wage function is expressed

$$w_j(\theta,\phi) = \arg\max_w \left\{ \left(\overline{V_j^E}(\theta,\phi) - \overline{V_j^N} \right)^{\alpha} \left(\overline{V_j^F}(\theta,\phi,w) \right)^{1-\alpha} \right\}. \tag{1.4}$$

Given this function, it can be shown that the wage for a group j worker in a match defined by (θ, ϕ) is

$$w_j(\theta,\phi) = \frac{\alpha \left(\frac{d\overline{V_j^E}}{dw} \right) \left(\theta - \lambda^c \left(1 - F_j^*(\theta,\phi) + \phi \right) c^q \right) - (1-\alpha) \left(\frac{d\overline{V_j^F}}{dw} \right) \left(\overline{c} + \rho \overline{V_j^N} \right)}{\alpha \left(\frac{d\overline{V_j^E}}{dw} \right) - (1-\alpha) \left(\frac{d\overline{V_j^F}}{dw} \right)}, \tag{1.5}$$

where $\overline{c}$ is firms' expected disutility value for workers who will accept the wage offer.

If quit rates were constant with respect to the wage, the derivatives of the value functions for the employee and the firm would be equal to one and negative one respectively, and the complex quit probability expression could be replaced by a constant, say λ^q. In this case this expression would reduce to something resembling the familiar bargaining result: $\alpha(\theta - \lambda^q c^q) + (1-\alpha)\left(c + \rho V_j^N\right)$. However, in the present case, an increase in the wage does not only transfer instantaneous flow value from the firm to the worker; a wage increase also reduces the probability that a future cost draw will induce a quit, increasing the expected duration of the match and conferring some additional value on both parties. Firms therefore have some incentive to offer a wage that is higher than would otherwise be optimal in order to keep quit-prone workers on the job.

Note that if firms expect too high an $F_j(c)$, they may not make an offer where it would in fact be mutually beneficial; if their expectation is too low, they may make a losing offer. This means that in general, more quit-prone workers (e.g., single mothers) and fewer low-quit workers (e.g., childless women) will be employed than in a full-information setting. This increases the overall churn rate of the workforce relative to the full-information case by bringing in workers who are more likely to quit.

Within gender groups, family structure subgroups with greater expected flow disutility from employment will have a smaller V_j^E and a larger quit rate at any wage level than firms project, while subgroups with smaller expected disutility experience the opposite. The direction of the net effect of these misalignments — the effect of statistical discrimination — on wages is theoretically ambiguous. In fact, it can be shown that the direction of the wage effect depends on α.[21] In most applications of statistical discrimination theory, it is assumed that firms are discriminating on differing productivity, so that the direction of the predicted wage effect is obvious. Here, however, the differentiating characteristic, proneness to quits due to family instability, also impacts workers' reservation wages — a more likely quitter must also be paid more in order to agree to work in the first place. Thus, firms may statistically discriminate without having a discernable effect on wages. As I discuss in

[21] This is essentially because α determines how close the bargained wage lies to the negotiating floor, the reservation wage. If α is small and the wage is close to this floor, and a shift of $F_j(c)$ raises the floor, wages will also rise. This implies the opposite possibility — a reduction in quit rates could result in lower wages if firm bargaining power is great enough. In another paper, I demonstrate that child care subsidies are estimated to have no statistically significant effect on wages overall. However, when I include an interaction of subsidies with a proxy for worker bargaining power, state-year unionization levels, results predict that wages decrease where worker power is low and increase where it is great.

Section 1.3.2, though, there are other dimensions along which this type of discrimination can be detrimental. A strength of this theoretical model is that it allows for examination of the effects of discrimination via multiple channels.

1.3.2 Layoff Frequency: Discussion

This model can generate the kind of layoff rate variation displayed by the data in Section 3.4 because the degree to which quit rates impact the value of an employment relationship varies with the associated layoff rate, and vice versa. In the case of a low-layoff job, the difference in expected duration of employment between individuals with quite different quit rates will be significant, with a higher quit rate reducing expectations a great deal. The difference would be much less significant at a layoff-prone job, which will be short-lived regardless of employee quit probabilities. In addition, firms looking to fill high-ϕ jobs will not anticipate significant costs if the applicant they choose to fill that position quits. All this causes firms with layoff-prone openings to mostly disregard quits. Inversely, a rare-quits individual will value a rare-layoff job relatively more than a quit-prone individual will. The hiring effect is particularly consequential in the context of statistical discrimination. Rare-layoff firms will be more reluctant to hire female workers, pushing them toward layoff-prone jobs *regardless of their actual propensity to quit.*[22]

Such a relative shift in hiring does not imply directly that the *frequency* of layoffs — the empirical outcome measure on which I focused in Section 3.4 — will be greater among workers with greater (or perceived greater) disutility distributions F_j. However, child care policy that increases women's labor market attachment appears to reduce the frequency of

[22]This should be reflected in the data in wages: group quit rates and occupational layoff rates ought to reduce wages, other things equal, but the interaction of these rates should dampen the effect, so that the quit probability drags wages down less in a layoff-prone job and vice-versa. In results not included here, I show that this pattern is present in the SIPP data: group quit rates and occupational layoff rates indicate lower wages, but their interaction effect is positive and negates approximately one half of their added specific effects.

their layoffs, not merely alter the types of positions they fill. This is simply because, though statistical discrimination drives them toward layoff-prone jobs, these workers do not quit — they stick around until the high ϕ on their jobs generates a layoff. Thus, the model predicts that childless women would experience the largest decrease in measured layoff rates due to child care policy changes, just as demonstrated in Section 3.4.

1.4 Identification and Estimation

In this section, I estimate a version of the theoretical model from Section 3.2. To support identification of parameters of interest, I make certain adjustments to the model. I discuss these adjustments, the estimation procedure, and identification in Section 1.4.1. I report results of the implementation of the model in the SIPP data in Section 1.4.2. The estimates allow me to perform the counterfactual exercises described in Section 1.4.3.

1.4.1 Estimation Approach

Model Adjustments

In estimation, I replace the full subgroup distributions of disutility of work with a fixed base reservation wage and variable individual quit rates, allowing the worker's quit rate to depend on demographic and human capital covariates, the use of child care and subsidies, and the value of available subsidies. I estimate this quit rate equation outside the main structural model as a first step. I also exclude the wage from the equation determining the probability that an individual will quit due to family concerns. That is, the probability of a quit is determined by demographic characteristics and relevant child care variables: the presence of children, use of child care services, takeup of a subsidy, and the available subsidy amount. The disutility of work is therefore a constant reflected in the reservation wage.

While disutility distributions are useful in the theoretical model for an intuitive description of how adverse events at home can generate quits, the main concern in estimation in this case is the importance of the spillover effect from changes in mothers' quit rates on childless female workers, rather than the mechanism generating the quit rates themselves.

These adjustments dramatically simplify estimation and in particular identification. Specifically, restricting the relationship between wages and quit rates to a single direction — higher quit rates lead to lower wages due to greater expected costs to the firm — permits identification of the size of that relationship, which is the relevant cost of separations to the firm. This is a result of a tradeoff in estimation of the model: I can either fix the cost of separations, determining the way in which varying quit rates reduce wage offers, and estimate the reduction of quits coming from wage increases, or fix the latter value and identify the former. I choose to estimate firm costs because this is the model parameter determining the size of spillover effects from any change in subgroup quit rates. Essential features of the theoretical model remain; child care policy can be allowed to affect quit rates for relevant subgroups, and these effects have their impact through changes in the expected duration of an employment relationship, not through the periodic productivity of that relationship.

Whether an individual i quits a given employment spell of occupational group m in month t is thus specified as a probit in which a quit occurs if $Q_i^* \geq 0$:

$$\begin{aligned} Q_i^* = {} & \beta_1 + \beta_2 \left(group_i\right) + \beta_3 \left(race_i\right) + \beta_4 \left(SC_i\right) + \beta_5 \left(age_{it} \geq 40\right) + \\ & \beta_6 \left(CCuse_i\right) + \beta_7 \left(kids_i\right) + \beta_8 \left(CCrec_i\right) + \beta_9 \left(CCrec_i\right) \times \left(CCsub_i\right) + \beta_{11,m} + \varepsilon_{it}, \end{aligned} \tag{1.6}$$

where the vector $race_i$ includes dummies for respondents declaring black or African American as their race or Hispanic ethnicity, the vector SC_i is a dummy for postsecondary education less than a bachelor's degree, $kids_i$ is a count of children in the household, subscript F

indicates that the value is dependent on the firm or job involved in the match, $\beta_{11,m}$ is a vector of coefficients corresponding to the occupational group dummies (with high-end services the excluded group), and ε_{it} is a standard normal error term. $CCuse_i$ records whether the worker utilizes some form of child care — subsidized or not — while employed in the given spell. $CCrec_i$ is an indicator for receipt of a child care subsidy, and its interaction with $CCsub_i$ represents the maximum available value of those subsidies to recipients given the state and year of the start of the employment spell.

This alters the expressions of the value of each employment state and the bargained wage. Fully simplified and expressed in discrete time for estimation, the wage is now

$$w_{iF} = \alpha \left[\theta - \left(\lambda_j^F + \phi_F - \lambda_j^F \times \phi_F\right) c_\phi^q\right] + (1-\alpha)\, w^*. \tag{1.7}$$

Equation (1.7) permits more explicit examination of the theoretical claim made in Section 1.3.2 that individuals with high (perceived) quit probabilities will be relatively more attractive to firms with layoff-prone job openings. First, note the subtraction of the term $\lambda_j^F \times \phi_F$, which represents the probability that both a quit and a layoff will occur randomly in the same discrete period.[23] A larger value of ϕ_F deflates the negative impact of increasing λ_j^F on the bargained wage because a layoff may intervene before a quit can occur in any given period. In addition, costs of separation are lower on short-term jobs (as represented by the ϕ subscript on c^q). The decrease in wage offers due to quit probabilities will thus be smaller at layoff-prone firms, making matches with quit-prone workers relatively more likely. This is key in generating the effect demonstrated in Section 3.4 that child care subsidies reduce layoffs for childless women, since reducing women's overall average quit rates also reduces the degree to which layoff-prone firms and female workers are relatively more attracted to one another.

[23] In continuous time in the theoretical model, this value was assumed to shrink to zero.

The effect on childless women of course arises due to statistical discrimination. In estimation, I collect all male workers into a single subgroup, while subgroups of female workers are divided by whether or not they have a child as well as whether they access child care and subsidies. Female workers differ in their quit probabilities based on the presence of children and their usage of child care arrangements and subsidies, but firms cannot differentiate along these lines in negotiations over θ. Instead, firms construct an expected quit probability as a weighted average of the subgroup rates given the wage offer, the job-specific layoff rate, state subsidy maxima, and the known proportions of mothers who use child care and subsidies. That is, firms know how frequently childless women, mothers who do not use child care, mothers who use child care but not subsidies, and subsidy recipients will quit at any wage rate, as well as the proportions of the female workforce those groups represent, and thus can derive an expected quit rate. This creates the potential for statistical discrimination — if quit rates vary widely within the female workforce, firms will underpay some female employees and overpay others.

The Likelihood Function and Estimation

Estimation is by maximum likelihood. The estimation procedure itself works as follows.

I collect monthly data into spells of employment and nonemployment and characterized by their lengths, whether they ended in-sample or were right-censored, the child care subsidy rate in the state of residence at the time the spell began, and the demographic information of the respondent. Employment spell records also include the wage level, the occupational sector (of the four job types described in Section 3.3), the worker's usage of and expenditure on child care subsidies and services during the spell, and whether the spell ended with a quit, a layoff, or some other event such as retirement. Each wage offer draw (accepted or rejected) must be characterized by an occupational category, so the probabilities q_{mj} that a draw of θ comes from job type m are estimated separately by gender group.

I assume that ϕ for each job match is drawn from a common discrete distribution with two points of support, $\{\phi_1, \phi_2\}$. I allow the probabilities assigned to each point in the distribution to vary across the four occupational categories. I also allow occupation type, workers' demographic characteristics, and the drawn layoff rate ϕ to affect the parameters of the productivity draw distribution, from which the θ characterizing the job offers are taken. Distributions are parameterized as lognormal, a typical assumption in the literature. The means of these distributions, denoted μ, vary additively with job type, gender, race/ethnicity, educational attainment, and job layoff rate shifters; the standard deviations, denoted σ, vary multiplicatively with the same set of variables. That these distributions vary by gender assures that the weight assigned to quit rates in the wage equation does not reflect any other wage effect associated with the gender groups into which firms divide workers when negotiating what to pay them; the case of variance by job layoff rate and the types of jobs associated with frequent layoffs. Occupational groups are designated by the notation ("high-end service" = 1, "mid-tier service" = 2, "low-end service" = 3, "manual" = 4), so that θ for an individual i who matches with an occupation-m employer (with probability q_{mj}, given a match) is distributed thusly:

$$ln\left(\theta\right) \sim \mathcal{N}\left(\mu_i, \sigma_i\right);$$

$$\mu_i = \mu_m + \mu_{fem}\left(female_i\right) + \mu_{min}\left(minority_i\right) + \mu_{sc}\left(SC_i\right) + \mu_{hi}\left(\mathbf{1}\left[\phi_i = \phi_2\right]\right)$$

$$\sigma_i = \sigma_m \times \sigma_{fem}\left(female_i\right) \times \sigma_{min}\left(minority_i\right) \times \sigma_{sc}\left(SC_i\right) \times \sigma_{hi}\left(\mathbf{1}\left[\phi_i = \phi_2\right]\right)$$

I fix certain parameters, found in Table 8: the layoff probability for the lower ϕ-type (ϕ_1) is .0019,[24] the probability of drawing the lower layoff probability ϕ_1 in manual work (denoted p_4 in accordance with the below notation) is 0.4, ρ is set so that the annualized

[24] This value is one half the proportion of total recorded employed periods in all spells during which a layoff occurred.

discount factor is 0.1, and α equals 0.3.[25] I fix the reservation wage at the lowest value permitted in the data, \$2.25, or the lowest state minimum hourly wage for tipped workers during the covered period. The lowest wage accepted in the data is a consistent estimator of the reservation wage (Flinn and Heckman, 1982). I assume that wage values are measured accurately.

The high layoff rate type ϕ_2 and the probability p_m for each job type m that the low ϕ-type is drawn are estimated separately based on the fixed ϕ_1 and p_4. I use the maximum likelihood approach subsequently used to estimate the remaining parameters, but the occupation-draw probabilities at their actual workforce proportions in the data and the μ and σ at values predicted by reverse-engineering θ values from data and initial parameter guesses and approximating the distribution of those θ with lognormal distributions. These assumptions allow me to pin down a value for ϕ_2 based on the actual rate of layoffs in manual work, and from there the draw probabilities in the other occupational groups. The fixed value of ϕ_2 is .0083 (over four times the lower layoff rate ϕ_1), and the probabilities of drawing ϕ_1 are set at .768 in high-end services, .696 in middle-tier services, and .585 in low-end services.

In order to identify firms' layoff rate-dependent separation costs independently from the wage effects of varying layoff rates themselves, I set the separation cost to be one tenth the size on short-term (ϕ_2) jobs of the estimated value on long-term (ϕ_1) jobs. That is, $c^q_{\phi_2} = .1c^q_{\phi_1}$. I arrive at a multiplier of .1 using a simple linear estimation of the relationship between turnover frequency and cost values for different industries presented in Table 2 of Manning (2006). Given the values of ϕ determined above, short-term jobs would be expected to generate about one tenth the turnover costs per turnover event.

The parameters that remain to be estimated are thus the probability λ^θ of drawing a

[25]This value is based on results from Flinn (2003) and Dey and Flinn (2005), which suggest that around 0.4 is a good estimate for α in the labor market overall, while 0.25 is a more reasonable estimate for workers in jobs with wages relatively close to the minimum wage, which are overrepresented in the focal sample here.

new wage offer, the gender-specific probabilities q_m that such a new wage offer comes from each of the four occupational categories, the parameters of the productivity distributions, the β vectors determining the quit probabilities for each group, and long-term job separation cost $c^q_{\phi_1}$.

Likelihoods are constructed for each spell in the data as the product of the likelihood that a spell of precisely its kind (e.g. with the given occupation and wage level) would be started, the likelihood that it would last exactly the number of months it did, and the likelihood it would end in the fashion that it did. If L is the full length of a spell, RC is a dummy for a right-censored spell,[26] θ^* is that productivity draw which generates w^*, θ^*_F is that productivity draw which generates the firm's gender-based conjecture for the reservation wage (w^*_F), and $G(\cdot)$ is the CDF of the productivity distribution at its argument, then for nonemployment spells the likelihood expression is

$$\mathcal{L}^N = \left[\left(\left(1-\lambda^\theta\right) + \lambda^\theta \left(G\left(max\left\{\theta^*, \theta^*_F\right\}\right)\right)\right)^{(L-1+RC)}\right] \times \left[\left(\lambda^\theta \left(1 - G\left(max\left\{\theta^*, \theta^*_F\right\}\right)\right)\right)^{(1-RC)}\right]. \tag{1.8}$$

The likelihood of an employment spell is more complex due to the presence of a wage and multiple avenues to exit the spell. First, the parameter guesses and wage value for the spell are used to back out a value for θ from the wage formula for each employment spell. Next, the following value is calculated for each spell:

$$p_\theta = \frac{g(\theta)}{1 - G\left(max\left\{\theta^*, \theta^*_F\right\}\right)},$$

where $g(\cdot)$ is the PDF of the productivity distribution at its argument and the entire value is replaced with zero if $\theta - \lambda^F c^q < w^*$ — that is, if there is no surplus over which to bargain. p^θ is thus the probability that, given that the productivity draw was sufficient to initiate a

[26]Relatively rare departures from work for retirement or school are treated as right-censoring in estimation.

wage offer as well as the job type from which the draw was made, the draw was exactly that value of θ derived from the parameter guesses and data.

Once these expressions are established, the likelihood of a completed or censored employment spell can be written

$$\mathcal{L}^E = p_\theta \left(q_{mj}\right) \left[1 - \left(p_m \phi_1 + \left(1 - p_m\right) \phi_2 + \lambda^q\right)^{L-D-Q} \times \left[\left(p_m \phi_1 + \left(1 - p_m\right) \phi_2\right)^D\right] \left[\left(\lambda^q\right)^Q\right]\right], \tag{1.9}$$

where D is an indicator for the spell ending in a layoff and Q is similar for a quit. I calculate these likelihood values for all spells in the data and maximize the sum of their natural logs.

Identification

The main identification concern in estimating this model will be the parameters of the wage equation. In particular, two questions arise: how can I be sure that firms are responding to quit probabilities rather than some other correlated factor in adjusting their wage offers, and how can I be sure that the response I estimate of wages to quit rates does not reflect the opposite causal relationship, quits caused by unsatisfactory wages?

Because what firms believe about applicants' quit rates comes entirely from factors exogenous to any single job match, like child care policy and population group averages of child care behavior, or variables which are also permitted to affect the productivity distribution directly — gender, race, and educational attainment — the impact of any of these other characteristics on the wage is identified and estimated elsewhere in the model. Firms' understanding of quit rates is not informed by any factors other than these because, by construction, it cannot be. One could argue that having subsidized child care does not only reduce the rate at which mothers quit, but increases their productivity by making them more reliable or providing them with peace of mind. In this case, estimates of the effect of quit rate reductions, as well as information revelation concerning quit probabilities, on wages and other contingent outcomes would be biased upward in magnitude. However, in this scenario any estimated effect could still be credited to child care subsidies and information about their usage per se rather than (or in addition to) its effect on quit probabilities.

Given α, the lognormality assumption on the distributions of θ allows identification of the parameters of those distributions as demonstrated by Flinn and Heckman (1982). λ^{θ} and the occupation draw probabilities q_m are identified by the length of nonemployment spells and the gender-specific probability that, given job offer acceptance, an employment spell starts with a job of a given type. Coefficients in the quit probability equation are identified by actual quit frequencies just as they would be in a regular probit. Once quit probabilities and distributions of θ are identified, c^q can be estimated from the relationship between wages and the rates of separation (quits and layoffs) known to firms.

1.4.2 Parameter Estimates and Model Fit

In order to focus the estimation results on somewhat more relevant groups of workers, I estimate the search model using a sample which includes only SIPP respondents with less educational attainment than a bachelor's degree. Having completed some level of college is allowed to shift the productivity distribution parameters and the quit probability.

Results from maximum likelihood estimation can be found in Table 9. The right-hand column reports the coefficients from the true quit rate function. All women's quit probabilities are significantly larger than those of men, but those of women with children are the largest, with a coefficient around 40 percent larger than that assigned to childless women. Moreover, mothers who use child care subsidies while working experience a large, though statistically insignificant, increase in their base probability of quitting, on the same order of magnitude as the difference between men and women. This is presumably because women who receive subsidies are more likely to quit for other reasons not captured by the other variables included in the model.

Given usage of a child care subsidy, however, the effect of larger subsidy maxima (β_9) is to reduce quit rates in a statistically significant way. For some perspective regarding the value of the coefficient, child care subsidy maxima range from \$50 to \$275 (on a weekly basis) in this data, though the vast majority of state-year values fall in the \$75-\$175 range. Parents who use child care and access subsidies are more likely to quit, but the generosity of subsidies counteracts this increase; probit estimates imply that it takes around \$110 per week of child care subsidization to fully alleviate the quit probability increase faced by female workers with children who are in position to use subsidies over and above the base quit rate of their childless female coworkers, or around \$200 to reduce recipients' quit rates to those of male workers.[27]

In the structural estimates, I note that female workers are estimated to draw from a productivity distribution with a lognormal mean barely (and insignificantly) larger than that of men, but the lognormal standard deviation is just 86 percent the size, indicating that women's wage distribution is concentrated at lower levels (and its true mean is smaller). Minority (black or Hispanic) workers suffer large mean penalties, while having some post-baccalaureate educational experience increases the lognormal mean by about 0.14 over a high school education. The productivity penalty on short-term jobs (coefficient values designated in Table 9 with a *hi* subscript, for high ϕ) is extreme, with a change in the lognormal standard deviation of 32 percent. Some of this is recovered due to lower expected costs of separation; replacing a long-term employee is estimated to cost \$2,498, while short-term employee replacement costs are set at one tenth of this value.[28] However, wages are on

[27]Though it reduces the statistical significance of the coefficients, a probit model in which a square term for the subsidy value is included yields a very small positive coefficient on that term — small enough that there is next to no decline in the power of subsidy generosity to reduce quits as that generosity increases within the range existent in the data. For this reason, I am comfortable using a linear term and extending counterfactuals to the maximum subsidy available in the data.

[28]Recall that this estimate comes only from the degree to which firms translate increased expected costs into lower wage offers, not actual estimates of true replacement costs.

average much lower on short-lived jobs.

In order to assess the impact of child care subsidies in the empirical model, I perform simulation exercises. To ease the computational burden, I discretize the estimated θ distributions as well as the true distribution of child care subsidy values, from which these simulation inputs will be drawn. Because spell durations and wage growth over time are of interest, I simulate 25,000 total individuals (5,000 each of identical men, childless women, mothers who do not require child care, mothers who procure child care but do not use subsidies, and subsidy recipients) for a total of 480 months while holding age constant at 30 for all simulated individuals for simplicity. I posit a post-retirement value identical to the present discounted value of 240 months receiving the value of the unemployment state. Since mid-career outcomes are of the greatest interest, establishing a reasonable retirement value simply allows for backward solution of the individual decision problem with regard to each possible wage offer, following the approach of Rendon (2006). In simulation, rather than fixing the reservation wage, I allow workers to account for their own calculated PDV of the nonemployment state when choosing to accept a wage offer. This increases reservation wages, and thus accepted wages, above the range suggested by the data, as we will see. However, it allows for a nuanced simulation of the dynamic optimization of workers as they navigate the labor market, one in which it is reasonable to expect short-term firms and short-term workers to attract one another as long-term firms (via wage offers) and long-term workers (via reservation wages) hold out to meet one another.

For each simulated individual, the following characteristics are drawn at period 1 and are permanent: race, number of children (if the individual is in a parent subgroup; either one or two children), child care user status, child care subsidy recipient status, and state child care subsidy maximum.[29] Each worker-job pair is characterized by a job type draw, a quit

[29]Because child care and subsidy user statuses are permanent, this is not a true life-cycle simulation, and the interest is in comparing across groups over middle-term windows of time.

probability based on the estimated parameter values, and a draw of the layoff probability ϕ based on the estimated probabilities for the job type. Workers compare the PDV of being employed at the offered wage given these separation probabilities and the PDV of the nonemployment state — this is different from the model, which assumes that the PDV of the nonemployment state is the fixed reservation wage, but facilitates extension beyond the comparatively short length of the panel for the examination of spell lengths and separation events more generally. Once employed, individuals draw anew each period against their quit and layoff probabilities and potentially separate from the job, reentering the nonemployment state. Wages are assumed to increase on a yearly basis during an employment spell up to the tenth year based on the following specification:

$$w(\omega, y_t) = \omega \cdot exp\left(.06y_t - .003y_t^2\right),$$

where ω is the initial wage offer and y_t is the number of years spent in the current employment spell as of period t. This specification roughly follows that estimated by Rendon (2006), but uses parameters set to match ten-year wage growth as estimated by Pavan (2011) — levelling off at around 34 percent growth over the initial wage after ten years of tenure. Simulated wage growth allows for results to be obtained with respect to the effects of employment continuity on periodic income, and is for these illustrative purposes only as it too increases simulated wage averages.

For reference, Figure 3 displays the time-paths of wages, employment rates, layoff rates, and quit rates by gender and, for women, parental status in the SIPP data, using a sample of workers lacking bachelor's degrees. Married men garner the highest wages, single mothers earn the least, and the growth of wages is meaningfully smaller for women and quit-prone groups — a difference of about $2 per hour in wage growth when comparing mothers to married men — over the course of the 30 year career. While men are employed at a rate of nearly 90 percent in both the data and the simulation, women with children work at lower rates, particularly at the ages at which their children are likely young. Finally, while layoff rates are much messier in both the data and the model, note that in the SIPP data interesting trends are present. Though men vastly overpopulate the high-turnover occupations of trades, manufacturing, and construction, men and women from similar family structures are laid off at relatively similar rates. At many ages, single mothers show the highest rate of layoffs and temporary work. Overall, layoff rates decline as workers age.

All these patterns are generally borne out in simulation, though women's employment rates catch up much more completely to men's over time in the model than in the data. These results are contained in Figure 2.[30] Wages and wage growth are greater for male workers, while quit rates are somewhat higher for female workers, in particular those with children.[31] Levels and trends regarding layoffs are also similar between data and simulation. In simulation, all subgroups of female workers experience similar outcomes, with the only variation on average generated by variant quit rates. Because mothers quit more often, they have to return from the unemployed pool more often, dampening their wages and employment rates somewhat; women without children fare slightly better on these measures, as in the data. In particular, mothers who need to use child care to work but are never-users of subsidies[32] have the highest quit rates. In the base simulation, subsidy recipients' quit rates are lower due to the size of subsidies available to some of these workers, so that their other outcomes are somewhat more positive.

[30] In this and all simulation figures that follow, I smooth the generated periodic quit rates, rather volatile month-to-month, in each group by taking the average over the 12-month period starting in each given month. This shortens the x-axis by 12 observations. I also focus on employment rates from months 120 to 360, since the simulants all start out unemployed and take time to settle into equilibrium with respect to employment status.

[31] The assumption regarding constant simulant age group, under 40, implies that the convergence of quit rates across gender with age shown in the data will not be present in simulation. All simulation results should be read as relevant for workers in the first half of their working-age life.

[32] Female workers who use child care are presumed to have a permanent characteristic dictating whether, if they are eligible, they will access subsidies. The proportion of such workers in the hiring pool is assumed by firms in wage bargaining to match that reflected in the true data.

1.4.3 Counterfactual Analysis

In this section, I explore changes in worker quit rates dictated by three counterfactual scenarios: one in which firms are provided with full information regarding applicants' quit rates, and two in which there are large changes in child care subsidy generosity. I closely examine the direct impact of subsidy generosity on mothers but also any spillover effect to childless women that arises.

Results from simulation in which firms are fully aware of each worker's quit probability are displayed in Figure 4. Note that in comparison to the base simulation, there is significantly more divergence in outcomes across groups of female workers as a result of their now-known divergent quit rates. In particular, there is a larger gap in layoff rates between unsubsidized child care users and childless women than between the latter and men. This demonstrates the first key feature of the model: higher quit rates do in fact spill over into higher layoff rates. This is in part because quits prevent workers from "sticking" in long-term jobs and continually recording employment on a low-ϕ job. This is the reason the gap between female workers who require child care services and childless women also increases over time — workers in the latter group stay in low-ϕ jobs longer. But their wage offers on those jobs are also much higher, the main contributor to the gap.

Figures 5 and 6 compare workers' outcomes in a scenario in which the cap on all child care subsidy amounts is reduced to zero to their outcomes when all caps are raised to the maximum value observed in the data, \$275 per week. The difference most obvious from these graphs is the precipitous decline in subsidy-users' quit rates, from between .8 and .9 percent per period to below even the level of male workers, about .1 percent.[33] The remaining

[33] While this simulated example appears extreme, recall that a quadratic term in the quit probability equation suggests little change in the effect of subsidies throughout this range outside of the decrease in marginal effect from the probit specification. A smaller change in quit rates simply generates proportionally smaller changes in other outcomes, as suggested by the base simulation in which the true distribution of child care subsidy values is used.

relevant differences in outcomes are more legible in Table 10, which reports mean outcomes for months 120 to 360, the middle 20 years of the simulation, for all four scenarios (the base simulation, full information, and two extreme values of the subsidy maximum). Outcomes for men are the same across all scenarios because, in this model, only female workers differ along quit rate lines and may be affected by the policy changes.

While subsidy generosity changes do not directly cause quit rates to change for non-recipients, employment rates are greater for all female workers in the generous-subsidy scenario, by 0.7 percentage points for childless women and 1.9 percentage points for mothers.[34] Mothers' employment rates increase more because those who use subsidies are *in fact* quitting less often, but the increase across groups of female workers occurs for two reasons. Because firms see a decreased average quit rate for *all* women and they do not differentiate within the female applicant pool, all female workers seem more attractive to hiring firms, and wage offers increase. This attracts more childless women, for whom nothing else has changed, to the labor market. However, this increase in wage offers does not occur equally across the long- and short-term sectors. Since replacement costs are low on short-term (that is, high-ϕ) jobs, wage offers to women applying for these jobs were already only marginally penalized for the threat of a quit. But firms hiring for long-term positions offer a more dramatic wage increase. This pulls more female applicants toward such jobs, even those who were already on the labor market but relatively attracted to short-term jobs.

This implies a net increase in the number of workers employed in long-term jobs in the economy as a whole. In the context of this model, this is a result of its partial equilibrium setup. However, consider the possibility that many jobs can be performed either by a series of temporary workers or by a single more permanent worker, and that firms may convert some jobs from one to the other as it suits them. In the low-wage service industry, firms may

[34] Mean outcomes for mothers in Table 10 are a weighted average across the simulated groups, with the weights being the relative proportions in the SIPP data of women in each group to the total number of mothers.

consider treating some jobs as permanent hires rather than temps if they believe applicants are more likely to stick around. Again, imagine that firms are hiring for multiple jobs with different layoff rates ϕ. The differential wage offer increase seen by the model can occur within firms, indicating that these firms are "opening" more long-term jobs in the sense that they are willing to hire a wider pool of applicants for such jobs. The model is thus replicating this theoretical effect, if crudely so.

The employment rate effect can of course also be seen, most importantly, in the decrease in childless women's on-the-job layoff rates in the generous-subsidy scenario, from 0.271 percent to 0.257 percent. While this decrease appears small numerically, it represents approximately 5.2 percent of *all layoffs* and temporary-work separations among low-education women. This is of course an economically meaningful difference, and one that must be considered in analysis of the effects of child care subsidization policy. Consider that the results reported in Section 3.4 suggest that, for low-education workers, the reduction in quits among mothers and layoffs among female workers more generally in the face of a one-standard-deviation increase in the subsidy maximum are around the same magnitude, approximately a quarter of the base quit rate. Simulation results suggest that a reduction of about 18 percent in mothers' quit rates (from .68 percent per month to .56 percent), by whatever mechanism, can result in a 5.2% decrease in layoffs for childless women, very much on the same order of magnitude. Thus, the model seems to suggest that the contribution of such a mechanism can be quite substantial.

1.5 Conclusions

In this paper, I develop a job search model which directly incorporates variable probabilities of quits and layoffs into the structure of labor market decision-making. I demonstrate that such a model predicts nuanced links among quit probabilities, wages, and layoff rates, and that information asymmetries can result in spillover effects within gender groups because quit probabilities are not observable individual characteristics. SIPP data suggest that not only can reliable child care, enhanced for low-wage workers by subsidies, reduce the probability that a mother will be forced to quit her job, but firms may be aware of this effect and alter their treatment of female employees in response. Results from estimation of the model imply that employers looking for long-term employees are somewhat wary of female workers, but become less so when the surrounding policy environment suggests that they will be less likely to quit of their own volition. These conclusions have implications for policy designed to enhance labor market attachment for some group of workers, including explicit child care policy but also conceptually related programs such as the Earned Income Tax Credit and even health care policies that reduce health-related absences or separations from work. In an environment in which firms believe their employees will be able to continue working for them long-term — especially if there is a meaningful cost of separation — the nature of employment relationships is altered. One result may be that described by Barron, Black, and Loewenstein (1993) — those employees receive more on-the-job training — while another may be that they endure job destruction less often. In fact, these results go hand in hand.

Counterfactual simulations with full information demonstrate that statistical discrimination helps quit-prone workers who can pool with workers who are unlikely to quit due to asymmetries in information, but hurts those other workers, and that these impacts include a convergence of proportions in short-term work across groups. Additional simulations incorporating varied child care subsidy maxima reveal that a policy that reduces the quit probabilities of a small subgroup of workers can improve outcomes for any workers affected by such statistical discrimination. More investigation remains to be done into the relevance of bargaining power to the ways in which statistical discrimination, and any policy that affects reservation wages, *can* affect various worker outcomes. Future research could ask whether other policies that enhance labor market attachment, such as improved public transportation or health care, improve or diminish wage outcomes for affected workers, and whether this reflects bargaining power. In any case, the results in this paper point to the impact of policy remedies for issues that give rise to statistical discrimination, further leveling the labor market playing field. They also reveal the importance of policy impacts beyond the target or recipient population in the face of labor market issues affecting broad demographic groups, such as discrimination.

Chapter 2

Rational Responses to Uncertainty? Understanding Disadvantaged Youths' Educational Choices

This chapter is joint work with Nicholas W. Papageorge, Stefanie DeLuca, and Seth Gershenson.

2.1 Introduction

Despite increases in postsecondary enrollment by disadvantaged groups, gaps in final educational attainment across demographic and socioeconomic lines remain a significant issue (Bailey and Dynarski, 2011). Given these trends as well as prior research (Rosenbaum, 2015; Gershenson, Holt, and Papageorge, 2016), it is clear that there is a growing population of individuals who start postsecondary education but never attain a bachelor's degree. An

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emerging literature demonstrates that sub-baccalaureate credentials have highly variable returns, sometimes zero or negative on net (Cellini and Turner, Forthcoming). As we will show in this paper, this issue is disproportionately concentrated amongst low-income and minority students. While a significant body of research, including that by Keane and Wolpin (2001), Bettinger et al. (2012), and Hoxby and Turner (2015), has been dedicated to the question of the enrollment gap, somewhat less is known about what causes students who start postsecondary programs to attain less valuable credentials or drop out entirely.[1] Moreover, the extent to which students' beliefs about college completion given enrollment, which as this paper demonstrates also vary across sociodemographic groups, affect their decisions about whether and where to enroll is unclear. For instance, students may be concerned that issues at home, such as the illness or incarceration of a parent, might force them to take a break from school, which may violate financial aid or degree requirements or simply increase the barriers to continuation of the pursuit of a degree, or to drop out. In this case, students' subjective prospects for degree completion are reduced, which may affect application and enrollment decisions. Rather than a deficiency of information or resources, then, this would represent a rational response to uncertainty. Policies designed solely to address financial constraints, insufficient academic preparation, or lack of information will not represent a solution to this kind of issue. The sociological literature, including research by Holland and DeLuca (2016) and DeLuca, Clampet-Lundquist, and Edin (2016), shows that low-income and minority youth in fact do seek out short-term postsecondary credentials while harboring significant concerns about the probability that negative events will derail their efforts to succeed. A rigorous assessment of the decision-making process potentially mediating these facts remains to be performed.

One purpose of this paper is to provide evidence that young students develop rational

[1] Dynarski (2003) and Stinebrickner and Stinebrickner (2008) do report mixed results on the effects of resources on persistence at college, and Ellis and Gershenson (2016) document the impact of a college campus mentoring program.

expectations for postsecondary credential completion based not only on their demographic characteristics and academic ability but also their sense of instability in their own lives, and that they apply these expectations in making decisions about postsecondary schooling. In particular, we suggest that students with a history of frequent traumatic or disruptive life events, which we will call "adverse shocks" and which could potentially derail an educational trajectory, are likely to forecast more of these events in their own future, that these students adjust their subjective educational attainment expectations (downward) accordingly, and that these attainment expectations affect their decisions regarding enrollment. Because credit constraints and information and resource deficits, as documented in the above-cited literature, seem to explain some but not all of the attainment gap, and because adverse shocks are not evenly distributed throughout the student population, this research potentially fills a gap in our understanding regarding sociodemographic attainment differentials.

However, as we will show, the data regarding attainment expectations that is currently available in nationally representative surveys makes it difficult to identify the relationship between those expectations and informative past shocks on the one hand and enrollment decisions on the other hand. We can fix ideas with a brief example. This paper makes use of the National Longitudinal Study of Youth, 1997 (henceforth NLSY), in which high school students are asked to assign a percentage between 0 and 100 to the probability that they will earn a bachelor's degree before turning 30 years old. Their responses are of course some measure of their expectations regarding educational attainment. However, a number of component subjective probabilities are subsumed in this single question - the probabilities students assign to application to, acceptance by, and enrollment in specific postsecondary programs, the probability of degree attainment given enrollment in certain programs even without adverse shocks, the probability that adverse shock events will occur while students are enrolled, and the probability that these events fully derail their educational paths. Because we are particularly focused in the formulation and use of these last two objects, the

NLSY survey questions are not specific enough to satisfactorily identify the relationships of interest.

Thus, another goal we undertake in this paper is to describe, in a specific and useful way, the information which must be gathered in order to rigorously assess the effects suggested by the evidence we do provide, as well as the approach to this data-gathering process. This approach will be informed by a variety of research modalities. First, a simple structural model of the educational decision-making process will be formulated. This model will be used to highlight the important parameters which cannot be identified using available data, but also potential entry points for impactful policy responses to the effects of adverse shocks and expectations on the attainment gap. And second, a survey methodology will be constructed which permits the investigation of the relevant processes while also pinpointing potential confounders and sources of endogeneity in a way not sufficiently achieved in currently available data sets. In explicating this methodology, we will note the valuable interplay of various research techniques which permit a more complete and thus more detailed view of the decision-making process in question. As we note below, we hope that the example of this interdisciplinary, interactive, iterative approach can be applied in other dynamic-choice-related research contexts.

The paper proceeds as follows. We examine the relevant economic and sociological literature in Section 2.2 and describe the essential characteristics of the data we utilize in Section 3.3. In Section 3.4, we provide results from these nationally representative data sets which suggest a certain explanation for the attainment gap, demonstrating that attainment expectations are related to shocks both past and expected, educational decisions, and final attainment. We model decision-making in increasingly rigorous ways in Section 2.5, utilizing a two-stage least squares (2SLS) framework to provide more evidence of the impact of instability on expectations and in turn on attainment, as well as laying out a structural model of a high school student's educational decision. However, there are significant identification issues in each case owing to the nature of the available data. Rather than gloss over these concerns, in Section 2.6 we argue that these issues present an opportunity to test the merits of a cross-disciplinary approach to the formulation of surveys and interview protocols and the gathering of data, and describe methods which can be used to do so. This approach includes standard survey questions, cognitive interviewing techniques, and open-ended interviewing, all informed by economic modeling. Section 3.5 concludes.

2.2 Relevant Literature and Contributions

The vast majority of today's students not only graduate high school and plan to attend college, but actually enroll in some kind of higher education after graduation (Bailey and Dynarski, 2011). Rosenbaum (2015) find that, in a recent cohort, nearly 90 percent of high-income students enrolled in college after high school, as did three quarters of low-income students. While this represents a dramatic increase in *enrollment* over past generations, degree *completion* remains an issue. Only about half of students who attempt to earn a postsecondary credential of any kind actually complete one (Ma, Pender, and Welch, 2016). Minority students are particularly subject to this phenomenon; Snyder and Dillow (2011) find that only about 40 percent of African-American students who enter college receive a bachelor's degree within six years of starting a program, compared to 62 percent of white students. Those authors also note that only 20-30 percent of public community college students complete associate's degree programs within three years of beginning their studies. As we show below, the set of such outcomes (labeled "some college") is now the modal result for individuals who enroll in some kind of postsecondary program. These students eventually experience economic outcomes quite like those of high school graduates without any college — Hillman (2014) shows that they are more likely to be poor, to be unemployed, and to default on student loans than students who complete their degrees, while earning substantially less.

While these gaps reflect the financial and academic challenges disadvantaged youth face, they also reflect another growing trend: most poor and minority youth never enroll in four-year colleges at all. Instead, they are increasingly found in shorter-duration programs at for-profit institutions like occupational colleges and trade schools (Ma, Pender, and Welch, 2016). In fact, as recent work including that by Cottom (2018) shows, low-income students are three and a half times more likely to enroll in for-profit institutions than higher-income students, and more students of color begin their postsecondary education in for-profit institutions than in public or private two- or four-year schools. Yet relatively little literature examines how these decisions regarding enrollment are made. We aim to fill this gap by identifying how low-income minority students choose postsecondary programs, understanding student perceptions of returns, estimating the extent to which these perceptions can explain their choices, and examining whether they would make more optimal ones given more counseling and support while applying, or more flexible policies after they enroll.

Previous research has approached questions about unequal educational attainment primarily by hypothesizing that students encounter financial constraints or a lack of information or parental support (Attewell, Heil, and Reisel, 2011; Perna and Li, 2006; Keane and Wolpin, 2001; Dynarski, 2003). For example, students might be unaware of how to obtain funding for school or fail to recognize the relatively high returns to a four-year college degree versus one from a community college or a for-profit trade school (Bettinger et al., 2012). Specifically, Hoxby and Turner (2013) find that providing targeted customized information about college choices, cost, and application processes increased the quality of the colleges high-achieving low-income students attended, and reduced their college costs. However, their experiment focused on four-year college-bound high-achievers, so it is unclear if such findings would extend to students opting for other sub-baccalaureate pathways. In fact, Deil-Amen and

DeLuca (2010) show that in high school, counseling for middle- and low-achievers concerning sub-baccalaureate programs and career options tends to be inadequate.

While all these issues remain important, we explore another possibility, one that explicitly acknowledges how the neighborhood and family contexts in which low-income youth grow up might shape their educational choices. Our hypothesis is rooted in a combination of economic theories of rational dynamic investment decisions, in which individuals make optimal choices under constraints, and ecological models of human development which acknowledge the importance of social settings in explaining life course outcomes (Bronfenbrenner, 1977). Specifically, family socioeconomic background is a powerful predictor of educational attainment, but the role it plays extends beyond financial resources. Research concerning food and housing insecurity among college students (Goldrick-Rab, 2016), eviction (Desmond, 2016), and mass incarceration (Alexander, 2010) all point to the pervasiveness of family and community instability. DeLuca, Clampet-Lundquist, and Edin (2016) document that low-income African American youth frequently experience what we call "adverse shocks," such as family members and friends being evicted, arrested, incarcerated, injured, hospitalized, or killed. Any one of these events could require a student to take time out of school to grieve, support other family members financially, or both. This literature motivates us to rigorously test whether and how such shocks and instabilities shape students' postsecondary decision-making.

We thus contribute to the varied literature examining schooling decisions under uncertainty, and in particular the role of attitudes and beliefs about the future in the decision-making process. Belzil and Leonardi (2013) provide evidence that individual risk aversion deters investment in higher education. Wiswall and Zafar (2015) demonstrate that college students' choices of major are a function of their beliefs with regard to typical starting salaries by major. More directly relevant to this paper, Raley, Kim, and Daniels (2012) show an association in the NLSY97 between higher subjective probabilities of young pregnancy and reduced enrollment in and persistence at postsecondary programs. Expectations regarding pregnancy are just one of the indicators of anticipated adverse shocks we utilize in the empirical analysis of educational expectations and attainment below, in which we make an attempt to account for at least some of the inherent endogeneity concerns. As Jacob and Wilder (2010) note, a great deal of literature dating back to the 1970's shows that educational expectations are a strong predictor of final attainment even conditional on many background characteristics. However, the nature of the relationship between the two — whether and via what channels it is causal — remains an open question. In this paper we attempt to provide some preliminary answers, but also to refine the question so it might more plausibly be answered fully, given additional information we specify.

Jacob and Wilder (2010) also show that high school students update their educational expectations over the course of their secondary school careers, most often downward, and that these revisions are more likely to be made by students with low socioeconomic status and academic performance, as well as students who have children during high school. Here, we demonstrate that this sort of trend may be related to these students' forecasts of instability in their own lives, especially as they are informed by adverse shocks, including those that occur during their high school careers. We do so in part using existing nationally representative data sets, described in Section 3.3.

2.3 Data

We utilize data from three sources: the NLSY, the Education Longitudinal Study of 2002 (ELS), and the High School Longitudinal Study of 2009 (HSLS). These data sets differ in salient ways, as summarized in Table 11. The NLSY has the advantages of reporting GPA on a yearly basis in publicly available files and (significantly for our purposes) including questions about students' expectations regarding adverse shocks in their own futures. These reported expectations can be included in models of educational expectations and decisions to more directly assess the relationships of interest. On the other hand, the ELS panel contains a report of educational attainment expectations at each wave, so it is possible to assess the adjustment of these expectations over time, in particular in response to adverse shocks and other kinds of events. Students who start but do not complete a postsecondary program are also asked to supply a reason for this derailment. In addition, the two surveys pose the educational expectation question in different ways: NLSY respondents supply a subjective probability, 0-100, of earning a bachelor's degree prior to turning 30, whereas ELS respondents state the specific level of education they expect to ultimately attain. Replicating the core of our analysis using each response type can thus serve to mitigate some concerns with regard to measurement error that may attend each. In Section 3.4, we show that all major results are quite similar across the two panels. The HSLS combines some of the advantages of each of these data sets as demonstrated by Table 11, but its respondents are not generally old enough to have graduated from a four-year college program — only 59 individuals report having done so, while a majority of respondents whose status is known as of the most recent wave are still enrolled in some kind of postsecondary school. Thus, we use some of the unique variables available in the HSLS, discussed below, to assess parts of the decision-making process, but cannot make statements about impact on outcomes and do not feature these data prominently elsewhere.

Tables 12 and 13 summarize key background and academic variables for the full NLSY and ELS samples, as well as for subsamples by actual final educational attainment. In the interest of space, the "Some Coll" column includes individuals who start a postsecondary program but never earn any credential as well as certificate and associate's degree earners. It is clear that in both panels, minority and low-income students are more highly concentrated in the low-attainment groups, and in particular only end up with half their proportional representation in the degree-earning group.[2] Mother's education, high school GPA, and test scores[3] bear the expected relationships with attainment as well.

Table 14 summarizes each panel's expectations responses for each sample and the same subgroups. The top panel in the table shows the proportions of ELS respondents in each group column who said in tenth grade that they expected their final educational attainment to be that in the given row. For instance, just 10 percent of respondents said they anticipated starting a postsecondary program but never earning a bachelor's degree, while 22 percent on those who never finished high school stated this particular expectation. There are two obvious trends: expectations are relatively accurate, and inaccuracies tend to be too optimistic. Subgroups which finish with less education clearly have lower average expectations for their own attainment. However, 62 percent of respondents who stopped school after earning a high school diploma believed in tenth grade that they would go further than that, including a full 40 percent who expected to earn at least a bachelor's degree. 50 percent of those who started postsecondary school of some kind but never earned a bachelor's degree believed in high school that they would do just that. Explaining why these individuals fall short of their own expectations is an important part of determining the role of expectations in decision-making.

The second and third panels of Table 14, summarizing expectations data in the NLSY, suggest an answer.[4] In the middle panel of the table, respondents are supplying subjective probabilities of earning a bachelor's degree by age 30, and have been divided into quartiles based on their responses. First, note again that while attainment expectations are positively

[2]Note that the NLSY intentionally oversamples minority and at-risk white youth, which accounts for the differences in overall representation percentages between the panels.

[3]Score values are standardized in the NLSY sample, but remain raw in the ELS.

[4]Response rates for the expectations question are much higher in the ELS than in the NLSY mostly because the latter survey asked for attainment expectations only from those students who were at least 15 at the time of the initial survey, and never repeated the question. Because the sample is otherwise representative, there is no selection concern with respect to the results from the NLSY for the 15-18 year old starting cohorts.

correlated with outcomes, many appear to be overly optimistic; 30 and 39 percent, respectively, of high school dropouts and those who stop school after high school graduation state in the initial survey that they project at least a 75 percent chance of completing a bachelor's degree, many of these stating unequivocally that they certainly would. The third panel, meanwhile, summarizes expectations with regard to the occurrence of other events in the one year following the first survey, for which respondents also supplied subjective probabilities on a 0-100 scale. These events include being the victim of a crime, being arrested, dying,[5] and becoming pregnant. The most obvious trend is that those who eventually complete a bachelor's degree report much lower subjective probabilities of all these events.[6] However, it is also valuable to compare the trends across attainment in both types of expectations. Specifically, note that in terms of expectations for educational attainment, the "some college" group resembles the "college" group quite a bit — in general, their subjective probability distribution appears to be about the average of that of the "high school" group and that of the college group, if not slightly greater. Yet in terms of expectations regarding adverse shocks, their expectations are nearly identical to those of the high school group, and quite different from those of students who eventually earn a bachelor's degree. This may suggest that, amongst those with greater concern about future adverse shocks, those who start a

[5]In all groups the average percent chance placed on death in the next year is clearly much higher than the true probability. There are large spikes, for this and any question requiring a probabilistic response, at 50 percent, but even removing individuals giving this response leaves an average subjective probability of death of over 10 percent, as many students supply round values like 5, 10, and 20 percent at the low end. This raises concerns about numeracy and students' ability to accurately characterize their expectations in percentages as noted previously; however, the concentration of expectations for adverse shocks at higher percentages is in fact correlated with other variables we would expect to generate such expectations, like low income and a history of adverse shocks, so we believe the relative values of these expectations represent useful information, if not the raw values.

[6]Interestingly, eventual degree earners assign just as high a probability to getting drunk in the next year, the other adverse event the NLSY asks about, as those with less final educational attainment - that is, unless race is controlled for. High-income and white students are both more likely to earn a bachelor's degree and more likely to expect drunkenness in the year after the survey, so there is some correlation between these two measures. However, after dividing the sample by race or income group, we find that an expectation of drunkenness displays the same pattern as the shocks reported here - increased adverse expectations among those with lower eventual attainment.

postsecondary program are the most optimistic about their ability to complete it — which is unsurprising — but they often fail to do so. It may well be that the very adverse shocks to which these students assign a high probability hinder their educational progress, and students who instead revise their educational expectations downward are in fact "correct" in this sense. Our primary aim in this paper is to assess this possibility much more rigorously.

Before moving on to more direct evidence concerning expectations and decision-making, however, we briefly document the reality of the issue at hand: recent data show that the crisis of enrollment, at which much previous research and policy has been aimed, has been mitigated to a significant degree, but in its place has emerged a crisis of completion. Figures 7 and 8 show that for minority and low-income students in the ELS, attending a postsecondary program of some kind but never earning any credential (denoted "Some PS") is now the modal outcome. This path is about 12 percentage points more common among minority than white students, and 15 percentage points more common among low-income than high-income students. Earning an occupational certificate rather than a degree is also more prevalent in these disadvantaged groups. While there are also more high school dropouts, this difference is relatively small, especially by race. In this paper, we provide one explanation for why students might both drop out of postsecondary schools and, knowing this risk ahead of time, choose to enroll in shorter-term certificate programs. The main concern, then, is not enrollment after high school, but completion of a valuable credential.

Why does this issue matter — more specifically, what is the meaning and effect of a "valuable credential"? The returns to a four-year degree over and above those to merely attending college or earning a lesser credential are in fact quite large. In the NLSY, among those employed as of the 2015 survey,[7] the average annual income of college graduates was nearly $60,000, while that of those who halted their education after graduating high school was just under $36,000. Importantly, workers with some postsecondary education but no

[7]Respondents were thus between the ages of 30 and 36.

bachelor's degree - whether they earned an associate's degree or not - had an average annual income of just around $40,000 - that is, not much better than their peers who never attended any postsecondary school. Certainly there are selection issues with this simple analysis, but it is clear that the so-called "sheepskin effect" of a bachelor's degree is likely quite strong, and there is no evidence that the benefits of any other postsecondary outcome are comparable. Students who attend briefer postsecondary programs are committing to often significant expenditures with little return. Next, we show that there is reason to believe these students chose such a path because they had doubts about their ability to complete a four-year program due to expectations of volatility in their own lives.

2.4 Empirical Evidence

In this section we use our three nationally-representative data sets to provide evidence of the following relationships: (1) educational attainment expectations are positively related to actual attainment even after controlling for a host of covariates; (2) one important avenue through which expectations can affect attainment is the decision of what type of postsecondary institution (public vs. private vs. for-profit; four-year vs. short-term) to attend after high school; (3) adverse shocks, in the forms of both past events and expectations for the future, are negatively related to educational attainment expectations even after controlling for a host of covariates; and (4) the strong predictive power of high-school performance for final attainment may in part represent the impact of adverse shocks on attainment expectations, and in turn the impact of attainment expectations on the incentives to work hard in high school.

2.4.1 Expectations and Attainment

Jacob and Wilder (2010) show that ELS respondents who expect to complete college are more likely to enroll in college. Yet our interest is in whether they are also more likely to complete college, so we investigate that here. Jacob and Wilder (2010) also suggest that the explanatory power of expectations for enrollment may have declined over time. However, they note that this is at least in part due to the fact that the variance of attainment expectations was lower in their most recent data, from the ELS2002. Because the NLSY survey collects expectations as a percentage chance of graduation rather than a categorical response, a decrease in variance may be less of a concern in the use of those data.

As we saw in Section 3.3, educational expectations are strongly correlated with attainment across the data sets. In order to at least suggest causality - that is, to suggest that students' expectations with regard to graduation influence their enrollment and persistence decisions - we control for growing sets of covariates, including demographics, socioeconomic background, adverse shock history, and academic performance, in linear probability models of college completion. The results can be found in Tables 15 and 16. In the NLSY (Table 15), the subjective percentages supplied by respondents are collapsed into quartiles. In both cases, the introduction of control variables reduces the magnitude of the estimated effect of expectations on graduation probabilities. However, that effect remains significant even after the inclusion of all the above-noted covariates.[8] The NLSY specification shows that believing one has at least a 50 percent chance of earning a bachelor's degree may be something of an inflection point, while estimates from the ELS suggests that an expectation of some college predicts no greater a probability of graduation than an expectation of just a high school diploma. This latter effect may in part be due to students who plan in 10th grade to

[8]The predictive power of expectations increases in the NLSY after academic performance is included, but this is likely due to a severe (and presumably selective) reduction in the sample size owing to the many missing test scores in this data set.

earn a vocational certificate or associate's degree and then carry out that plan. In any case, these results lend credence to the idea that expectations have a causal effect on eventual attainment.

2.4.2 Expectations and Postsecondary Institution Choice

It may come as no surprise that the type of educational institution at which a student begins postsecondary education has a significant effect on that student's final attainment outcome. However, since this choice of postsecondary path is a key mechanism by which we hypothesize that expectations impact attainment, it is important to establish as specifically as possible what final attainment looks like at the many different available institution types available to graduating high school students. Final attainment is summarized by the kind of postsecondary school respondents first attend after high school in Tables 17 (NLSY) and 18 (ELS).[9] A few patterns emerge across both data sets. First, not many students who start at two-year programs go on to attain a bachelor's degree. About a quarter of such students at public and non-profit institutions do so, while very few at briefer for-profits do so (11 percent in the NLSY and just 4 percent in the ELS). The failure of students who start at for-profit institutions to earn bachelor's degrees in fact carries over to their longer-term programs; less than 30 percent of students in *four-year* programs at for-profits attain that degree. Around half of for-profit students never earn any credential. Two-year programs at all kinds of institutions display this pattern, however. To be sure, there is certainly selection in terms of who applies to and attends such programs. But investment in two-year postsecondary programs and for-profit schools appears to be fairly risky.

In Tables 19 and 20, postsecondary institution type is included in multinomial logits

[9]The institution types include public (Pub), private non-profit (NP), and private for-profit (FP). The relevant program lengths are also included as separating group characteristics - programs are characterized as either four years or no more than two years.

for final attainment in each data set. Even in the presence of demographic, background, and academic performance[10] controls, the effects described above remain stark and significant. In particular, note that in both data sets, and statistically significantly in the ELS, for-profit two-year schools appear to increase the probability (relative to a public two-year school) of a certificate or associate's degree, but at the expense of the probability of going on to attain a bachelor's degree. Again, public and non-profit four-year schools have by a wide margin the highest rates of eventual bachelor's degree attainment. Keeping in mind that education at for-profit schools tends to be more expensive and entail more debt than comparable public programs, one might wonder if students in attendance were fully informed of their likely outcomes when they enrolled. However, in the next subsection, we provide another suggestion for why students might choose programs that lead to lesser returns by exploring the relationships among expectations, institution type choice, and adverse shocks in more depth.

If adverse shocks operate on institution type choice through expectations, though, expectations themselves must clearly have some effect on this choice. The multinomial logit estimates in Table 21 demonstrate the existence of this relationship in the NLSY. Those with higher expectations regarding final attainment in the first interview are significantly less likely to attend public two-year and for-profit four-year programs, and significantly more likely to start their postsecondary education at a public four-year school, even after demographics, socioeconomic status, and academic performance have been accounted for.

The HSLS contains a few specific variables of particular use in refining our answer to the question of what influences postsecondary institution type choice. HSLS respondents report their ninth-grade expectations with regard to the income they could earn with various levels of educational attainment, how sure they are in ninth grade that they are "capable" of completing a bachelor's degree program given enrollment, and, once they are in eleventh

[10]Due to sample size concerns, academic performance controls are included in estimation in the ELS only.

grade, how likely they think it is that they would qualify for financial aid in postsecondary education if they applied. All these questions refer to factors students might incorporate in their final attainment expectations, but which are not directly related to adverse shocks. Thus, if we control for them in a model of institution type choice, we can be more confident that any estimated effects of shocks or attainment expectations are related to uncertainty about future adverse events. In addition, HSLS report in ninth grade whether they plan to enroll in a bachelor's degree program in the first year after high school. We can thus use this variable to narrow the sample and assess what may cause such plans to be derailed. Postsecondary attendance is also reported by the type of degree pursued as well as the type of institution attended, permitting a more precise estimation of the actual decision being made by each student, along with indicators for taking a break before enrolling and the reasons for such a break. The relevant variables from the HSLS are summarized in Table 22. Adverse shock indicators in the HSLS have been summed for the intra-wave periods 2009-2011 and 2011-2016 for purposes of concision and clarity; the first sum includes indicators for absence of a father figure, changing schools, the death, illness, divorce, or unemployment of a parent, a respondent's own serious illness, having a child,[11] and having one's home foreclosed on, while the second period sum includes only indicators for the parent- and illness-related variables since these are the only relevant questions asked in the most recent survey wave.[12]

Results from estimation of a multinomial logit model of postsecondary program type choice in the HSLS are contained in Tables 23 and 24. In both cases the sample is narrowed to those respondents who stated in ninth grade (survey year 2009) that they planned to

[11] As discussed in more detail in Section 2.5, childbearing is both a particularly significant predictor of attainment and more than just an adverse shock - it has long-term effects and is potentially highly endogenous. However, its inclusion in or exclusion from this sum has no impact on the final results of this estimation.

[12] It might be noted that a smaller proportion of individuals say they are sure they could complete a bachelor's degree program than expect to complete one. The dummy variable indicating confidence in one's own ability is valued 1 only for those who report that they "strongly agree" with the statement that they could earn a degree if enrolled. Nearly half say so; most of the rest merely "agree" with this statement, while few students "disagree" with it, strongly or not.

enroll in a bachelor's degree program after high school. Table 23 demonstrates that despite the inclusion of variables indicating whether and why students take a break before enrolling postsecondary school, whether they are confident in their ability to complete a four-year program academically, and their confidence about qualifying for financial aid in addition to all the usual controls, attainment expectations have a statistically significant effect on the choice of degree program after high school, increasing the probability of enrolling in public or non-profit four-year programs at the expense of two-year programs.[13] The incorporation of shock variables in Table 24 reduces the sample to a great degree, but two results are pertinent: the estimated effect of expectations is still large and in the expected direction, and instability also has a significant effect on institution choice, increasing public two-year enrollment. It seems clear that, to the degree that the HSLS can be said to measure them, students' predictions regarding their own academic ability and financial aid eligibility are not driving the relationships among instability, attainment expectations, and outcomes.

Finally, we can examine the degree to which postsecondary institution choice accounts for the relationship between expectations and final attainment. Tables 25 and 26 report results from estimation in the NLSY of a multinomial logit model for attainment, given enrollment in some kind of postsecondary program. In Table 25, expectations are included as a predictor of attainment along with demographics, background, and high school GPA. A higher subjective probability of college graduation clearly has a positive relationship with the final true probability that an individual will earn a bachelor's degree, with any expectation over 50 percent increasing that probability in a statistically significant way, reducing the probability of never attaining any credential. When we incorporate institution type[14] in Table 26, however, note that these relationships are halved in magnitude and insignificant.

[13]Earnings expectations also have no impact on the significance of this relationship and are themselves typically insignificant predictors of program type choice (results available on request).

[14]The excluded category is public two-year school.

Demographic effects are not altered nearly as much. Meanwhile, attending a public or non-profit four-year school now significantly increases the probability of earning a degree. Results from similar estimation in the ELS tell the same story, if not more starkly: the estimated effect of expectations on attainment given enrollment is reduced by three quarters after the introduction of postsecondary school type. A probit model for whether a student remains enrolled in some program as of the last wave of the HSLS also shows that introducing program type halves the positive and significant effect of attainment expectations.[15]

It appears that institution type selection accounts for most of the impact of expectations, which precede that selection, on outcomes. A question of paramount importance, then, is how are expectations generated? Do they owe at all to patterns of adverse shocks?

2.4.3 Adverse Shocks, Decision-Making, and Attainment

Table 27 summarizes the rates of a wide variety of adverse shocks among NLSY respondents for the full sample and by final attainment.[16] Outside of a few parental issues (hospitalization, divorce, and unemployment), respondents with less final education are more likely to have reported all these problems during their teen years. In particular, having an absent father, changing schools, seeing someone shot, and parental incarceration seem to trend very strongly with final attainment.

Do these childhood shocks predict educational attainment expectations? Results from an ordered probit model of expectations in the ELS,[17] reported in Table 28, suggest that they do. Here, our adverse shock indicators are collected into sums within large categories: family shocks (absent mother or father and changing schools) and victimization shocks (feeling

[15] ELS and HSLS results available on request.

[16] The set of adverse shock variables in the ELS, as well as the patterns by final attainment, are quite similar and excluded here in the interest of space.

[17] Recall that ELS expectations are reported as an anticipated final attainment level, like a high school diploma or a bachelor's degree.

unsafe, high neighborhood crime rates, and being the victim of various crimes) during high school, and postsecondary shocks (divorce or death of parents, own or family illness, or being the victim of violence) which occur after graduation. First, note that the last type of shock do not have any relationship to attainment expectations. This makes some sense, as these shocks occur after expectations are collected, and any power a student's expectations regarding these events are likely to have with respect to educational expectations ought mostly to be captured by the student's record of past shocks. Second, in the presence of most of our control variables, both family and victimization shocks during high school have a significant negative effect on attainment expectations. Third, this effect is insignificant if high school performance is included in the model. What this may represent in terms of the possible effects of shock events will be addressed in the next subsection.

Because attainment expectations are gathered at multiple ELS survey waves, it is possible to estimate the effects shock events can have on changes in those expectations over time. Table 29 contains results from a linear probability estimation of a reduction in a student's attainment expectations from at least a four-year degree to any level less than a four-year degree. Victimization shocks have a persistent effect, increasing this probability even when all our covariates are included. This suggests that students are altering their educational expectations in response to negative events happening in their own lives.

Of course this may be because such shocks make it difficult to prepare for college or keep one's grades up in high school classes - in other words, students' actual probability of graduating college may drop because of negative impacts on high school performance, rather than increased subjective probabilities of future shock events, and a downward revision of expectations makes sense even without concern for future instability. However, the NLSY provides us with a way to test this hypothesis. As we saw in Table 14, expectations regarding future instability are higher among individuals who eventually attain less education, and it appears that revising attainment expectations downward in response to concern about future adverse shocks makes sense since those who fail to do so may be less likely to earn a degree even once they enroll. Table 30 gives some indication that the effect of instability expectations on attainment may operate in part through attainment expectations, since these are much lower for those with negative forecasts for their futures across all available types of potential adverse shocks. In addition, Table 31 reports results from ordered probit estimations of attainment expectation quartiles including expectations regarding other events and increasing sets of controls. The negative impact of student expectations regarding arrest, pregnancy, and death is persistent and significant, though reduced somewhat by the introduction of controls. Note as well that the size and significance of some adverse shock indicator coefficients is reduced from earlier results by the presence here of expectations regarding future shocks, suggesting that past shocks operate on attainment expectations in part through expectations regarding other types of adverse events.

Finally, we estimate a linear probability model of college completion including expectations concerning both adverse shocks and attainment, as well as demographics, shocks, and high school performance, as covariates. Results are reported in Table 32, and several patterns are of note. First, there is a negative effect of expectations regarding adverse shocks on the probability of graduation, but this effect is mostly accounted for by attainment expectations themselves, which thus appear to adjust, appropriately, for concerns about future instability. Moreover, the significant effect of attainment expectations persists through the inclusion of all our other covariates, including high school performance, though it is reduced somewhat. Last, some adverse shocks have significant negative effects on attainment, though these are somewhat muted in comparison to previous results once all covariates are included.

In this subsection, we have provided evidence that adverse shocks impact expectations with regard to future instability as well as educational attainment, and that in turn these expectations affect educational outcomes, in part mediating the relationship between shocks and final attainment. In Section 2.5, we attempt to assess these relationships in greater depth, acknowledging the obvious data and identification concerns.

2.4.4 Expectations and High School Performance

In some of the results in the previous subsection, high school performance (grades and test scores) appeared to account for the effects of shocks or expectations on final attainment. However, there are multiple explanations for why these performance variables might be related to attainment expectations in a negative way, and not all suggest that expectations are merely a byproduct of a decision-making process impacted only by ability. For instance, if reduced attainment expectations (possibly the product of past or expected future adverse shocks) reduce the projected value of enrolling in college in the first place, a student will have less incentive to perform well on those measures that most directly affect their ability to enroll - that is, grades and test scores. That is to say, a student who believes college is a risky proposition even with good grades and scores due to the likelihood of future instability may disregard the value of earning those grades and scores. This is one reason why we have referred to these metrics as "high school performance" rather than "academic ability" - instability in one's personal life can have an impact on educational investment, both directly and through its effect on incentives. Thus, the strong predictive power of grades and test scores for attainment may in part be one channel through which expectations *become* accurate, through something of a self-fulfilling prophecy.

To assess the possibility that this mechanism is in operation, the relationship between shocks and grades - particularly changes in grades over time, since these might be thought to reflect changing circumstances rather than innate ability - must be estimated. Final GPA is available in both the ELS[18] and the NLSY, and we attempt to proxy for pre-shock "ability" using 10th grade test scores in the ELS and 9th grade GPA in the NLSY. If adverse shocks

[18] The GPA variable used here is recorded categorically by half-points (e.g., 3.0-3.5) in the ELS.

and the attendant changes in expectations (estimated in the previous subsection) have a negative impact on grades, we would suspect that the mechanism described above is at work. In fact, we estimate that adverse shocks during high school do have such an effect. Tables 33 and 34 show that in both the ELS and the NLSY, respectively, adverse shocks are estimated to reduce final grades in a statistically significant way relative to our proxies for prior ability. In particular, an absent father, parental incarceration, feeling unsafe, and being victimized stand out as impactful shocks across both data sets.

2.5 Modelling and Identifying Educational Decisions

All the results discussed in the previous section are obviously only suggestive. We have said little about the actual educational decision-making process — whether past adverse shocks in fact translate into greater expected future volatility, how both relate to educational expectations, and how big a role these expectations play in educational choices. In addition, there are clear concerns about endogeneity when it comes to subjective expectations and actions taken based on them, which we describe in detail below. In this section, we push the empirical analysis and modelling into this uncertain territory in part to demonstrate what questions we can and cannot answer confidently as the data stand, and to suggest what further information would be necessary.

2.5.1 Two-Stage Least Squares: Assumptions, Issues, and Estimates

One of the most basic results discussed in Section 3.4 is that attainment expectations have an independent effect on final actual attainment. But given concerns about unobserved heterogeneity governing both beliefs and outcomes, as well as the possibility that some students have already made their decisions with respect to education at the time they are asked to assess their probability of college graduation and answer based on this (reverse causality), we need a more rigorous econometric approach. For instance, if a valid instrument for attainment expectations in a model of actual attainment could be found, these concerns would be alleviated. This is not a simple exercise, as Jacob and Wilder (2010) note. But while there are some issues which we discuss below, the variables in the NLSY recording subjective probabilities assigned to future adverse shocks have some promise as an instrument.

As shown in the previous section, much of the relationship between expectations regarding adverse shocks and attainment could be explained by (their impact on) expectations regarding attainment itself, and these probabilities are otherwise strongly related to attainment expectations. We might also think that subjective probabilities placed on things like being arrested or experiencing a pregnancy are likely to be less correlated with unobserved academic ability than subjective probabilities placed on college graduation (though admittedly not entirely uncorrelated). In this case, we have something resembling an instrument for a two-stage model regressing attainment on those expectations.

Before proceeding to the form of and results from such a model, however, we discuss in more detail the assumptions necessarily being made and their validity. First, we must assume that attainment expectations are sufficiently strongly predicted by the instability-related expectations variables we use as exclusions in the final model. Given our prior results, this is certainly true, particularly with respect to subjective probabilities regarding arrest and pregnancy.

Second, in a two-equation model of attainment and attainment expectations, we must assume that everything included in the second equation is exogenous with regard to the error in that equation. In particular, this means that once we control for demographics, background, and past instances of instability, expectations regarding future instability (arrest and pregnancy) are not correlated with omitted variables that pertain to educational expectations. This is unlikely to be strictly true; respondents may be influenced by their understanding of probabilities in their responses, there are likely personal characteristics which govern general uncertainty or fear about the future for which we cannot control but which impact all these subjective probabilities, and it is of course possible that a respondent's expectation regarding whether they will graduate (or attend) college causally impacts expectations with regard to instability. This last possibility is of particular concern, as it is easy to think of an individual who would not predict impending arrest or pregnancy if they believed they were about to enroll in college, but since they do not anticipate this educational event, the subjective probability they assign to these other events increases. In fact, such expectations and the decisions to which they are related could all be determined jointly. Without more detailed information about the process by which each respondent formulates their set of expectations, it will be difficult to alleviate this issue completely.

Third, we must assume that, controlling for demographics and past instability, expectations regarding future instability — specifically the ones which will appear only in the attainment expectations equation, those regarding pregnancy and arrest — do not have an impact on final attainment except through their influence on attainment expectations. We have some mixed evidence with regard to this assumption, which we cannot test perfectly. In Table 32 we also showed that the coefficients on arrest and pregnancy expectations are greatly reduced in size and significance by the inclusion of categorical attainment expectations in a model of college attainment. Table 35 attempts to express this finding in a slightly different way: here we see that the addition of instability expectations (in column 3) to a LPM of college attainment hardly changes the coefficients on attainment expectations at all. In contrast, the presence of demographic or shock event variables in the model noticeably reduces these values. In addition, the last column shows us that coefficients on arrest and pregnancy expectations are quite small and insignificant in such a model when all the other controls are included. This may serve to lessen our concern with regard to this third assumption.

If we make these three assumptions, it allows us to estimate a two-equation model like that contained in Table 36. Specifically, we estimate the two-equation system

$$Y = X\beta_{4X} + I\beta_{4I} + E\beta_{4E} + \varepsilon_4$$

$$E = X\beta_{5X} + I\beta_{5I} + F\beta_{5F} + \varepsilon_5,$$

where Y is the outcome (college graduation), X are demographic and background variables, I are reported instances of past instability in the respondent's life, F is our average subjective probability variable which represents expectations regarding future instability, and E is the raw subjective probability assigned to college attainment. We apply the assumptions discussed above and treat educational attainment expectations E as endogenous.[19] Taking a look at Table 36, we see that expectations regarding college attainment, estimated as the result of (among other variables) expectations regarding pregnancy and arrest to which they are negatively related, have a significant positive effect on graduation probabilities. In the end, these results are in keeping with key relationships we are seeking to show exist. However, given the nature of the data, we may remain concerned about the soundness of the assumptions needed to estimate this relationship, particularly with regard to the exogeneity of instability expectations in a model of attainment expectations. The actual process of expectations formation, key to our understanding of the impact of the expectations themselves, likely must be investigated in a more detailed way if the approach explored here is to be applied formally. One way to perform this investigation would be via estimation of a model of dynamic discrete choice like the one discussed in the next subsection. However, given the nature of currently available data, there are identification concerns with this approach as

[19]The subjective probability assigned to death in the next year is included in the equation for college graduation but not that for attainment expectations. Removing it or including it in both equations does not have an appreciable effect on the results.

well, concerns which we propose to remedy via the data collection described in Section 2.6.

2.5.2 A Simple Structural Model and Identification Concerns

Building on our preliminary and reduced-form analyses of the data, our structural analysis begins with a formal decision-making model. The model provides an explicit conceptual framework that relates beliefs about shocks, anticipated completion probability, and beliefs about returns to educational investments and student decisions. The analysis in Section 3.4 proposes possible relationships among variables as well; however, these relationships are somewhat ad hoc. The benefit of the structural model is that it allows us to use the economic theory of dynamic decision-making to represent and estimate what are often highly non-linear relationships between beliefs and optimal choices.

Suppose, for instance, that individuals have a choice set denoted $\Delta = \{N, C, T, E, I\}$, where N represents no action, C is attending college, T is attending a short-term institution like a trade school, E is entering the labor market ("employment"), and I is engaging in illegal activity that generates income. In any period t, any individual can choose any of the above actions, though certain states of the world will mechanically eliminate specific choices (e.g., once a college degree is earned, the individual will never choose C again because there will be no benefit to doing so). The choice of an individual i at time t, d_{it}, should be thought of as representing an *attempt* to perform the given action; it is not a guarantee that the action will be completed, as described below.

The set of state variables will be denoted Z, and the vector of their values for a given individual i at a given time t denoted Z_{it}. The full expression of this vector is

$$Z_{it} = \left\{X_{it}, S_i, y_{it}^N ... y_{it}^I, r_{i,t-1}, D_{it}^C, D_{it}^T, F_{it}^C, F_{it}^T\right\},$$

where X_{it} are demographic and background variables, S_i is i's childhood history of shock events which remains constant from $t = 0$ and thus is not indexed by time, the y_{it}^d are the total years spent in each state corresponding to action $d \in \Delta$, $r_{i,t-1}$ is the true outcome ("reality") of the previous period's choice $d_{i,t-1}$ (which again may not be identical to that choice), D_{it}^d are indicators for possession of a degree of type $d \in \{C, T\}$, and F_{it}^d are indicators for having dropped out of a school of type $d \in \{C, T\}$ (dropping out to be defined below). At $t = 0$, all these values are equal to zero except X_{i0} and S_i, which represent the "endowment" of i. All variables contained in X_{it} either are constants or evolve deterministically (e.g., $age_{it} = age_{i,t-1} + 1$).

Years in state d evolve according to the following simple formula for all $d \in \Delta$:

$$y_{it}^d = y_{i,t-1}^d + \mathbb{1}[r_{i,t-1} = d].$$

For $d \in \{C, T\}$, a failure indicator is generated by:

$$F_{it}^d = F_{i,t-1}^d + \left(1 - F_{i,t-1}^d\right)\left(\mathbb{1} d_{i,t-1} = d\right)\left(\mathbb{1} r_{i,t-1} = N\right)$$

That is, if i had failed out of school type d as of the previous period, that status remains, but if not, then the current failure indicator is equal to one if the previous period's choice was d but the true outcome was N (which as described below is the only possibility other than d), and zero otherwise. Finally, c^d represents the cost of choice d, and w^r represents the wage earned in true outcome r. It will be assumed that $c^N = 0$ and $w^N = w^C = w^T = 0$.[20] The costs of the other choices are functions of demographics, background, and whether the previous state was equal to the current choice: $c^d = c^d\left(X_{it}, r_{i,t-1}\right)$; the last stipulation characterizes switching or startup costs. Expected income in the working states (legitimate and illegal) is a function of demographics, background, the previous state, years of experience in the chosen

[20] In principle it would be possible to include work-study states like "CE" and "TE" to represent students who work while in school and thus do have positive income.

working state, and whether the individual has any degrees: $w^d = w^d\left(X_{it}, r_{i,t-1}, y^d_{it}, D^C_{it}, D^T_{it}\right)$. We expect, for instance, that w^E is enhanced significantly if D^C_{it} is equal to one.

The reality r_{it} generated by choice d_{it} is either equal to that choice or to N, the "no action" state. This is determined by a draw against the probability $\alpha^{d_{it}}$ for each state. That is, for action choice d, there is probability α^d that the action will not be completed and the final state will be $r_{it} = N$, and thus probability $\left(1-\alpha^d\right)$ that the action will succeed and the final state will be $r_{it} = d_{it}$. Obviously, α^N is irrelevant. We can assume that $\alpha^I = 0$. For choices C and T, a final outcome of N represents dropping out as defined above. For choice E, final outcome N represents failed job search and unemployment. These α are functions of all state variables: $\alpha^d = \alpha^d\left(Z_{it}\right)$. Thus, these probabilities of failure are the only values in the model which depend on i's history of shock events, which can serve as an identifying exclusion (more on this later).

All the tools to formulate the individual's value function are now in place. Letting Z^S represent the set of state variables not including the individual history of adverse shocks S, the value function is:

$$V\left(Z_{it}\right) = \max_{d_{it}\in\Delta} \alpha^{d_{it}}_{it}\left[u\left(N|Z^S_{it}\right) + \beta E\left[V\left(Z_{i,t+1}|Z_{it}, d_{it}, N\right)\right]\right]$$

$$+ \left(1-\alpha^{d_{it}}_{it}\right)\left[u\left(d_{it}|Z^S_{it}\right) + \beta E\left[V\left(Z_{i,t+1}|Z_{it}, d_{it}, d_{it}\right)\right]\right].$$

Here u is the flow utility from the real outcome of the current action choice and the expectation of future value is taken over the probability of next period's outcome given the choice that will be made based on the final state of the current period. β is of course the discount rate.

This value function can also nest other explanations for the attainment gap — available assets could be allowed to affect the cost function or an additional consumption choice, and information deficits could be captured by uncertainty or systematic errors in the expectation operator. As they concern adverse shocks and the probability of completing a degree, though, the objects of greatest interest are the α. They govern the riskiness of the available educational investments. However, there are some serious questions related to these parameters with which we must grapple before estimating the model in this fashion.

Issue 1: What are the α in theory? In the model above, the α are specified as known functions of a student's history of adverse shocks. But it could sensibly be argued that the model ought to differentiate between the *true* probability of failure and the *perceived* probability. The latter is obviously what enters decision-making processes. But the former is what can be measured in the data, even accounting for issues of selection. It is possible to write a model in which the true α are latent parameters about which students learn via S_i. But how much can be known about what this learning process looks like? Would it be possible to ask students direct questions that lead to a characterization of their probabilistic thinking and updating? We hope to address these questions as discussed below in Section 2.6.

Issue 2: What are the α in the data? Certainly, the quantities represented by the α in the above model are *related* to the subjective probabilities supplied by NLSY respondents with respect to their earning a bachelor's degree. Of course, we do not have similar variables representing expected success rates of other activities, educational or otherwise. But there is a more important issue with the nature of these data, which can be exposed clearly by adding detail to the example described in Section 2.1. In the NLSY, respondents are asked the probability that they will have a college degree by the time they are age 30. Suppose the respondent answers 40 percent. While this information is useful, it is difficult to understand what exactly it reflects about decision-making and household instability. It could be the case that a respondent has little interest in going to college because he'd rather pursue a career as an artist, and therefore places just a 40 percent probability on enrolling in college. In this case, he must be placing a 100 percent probability on earning a degree provided that he enrolls. Thus, household instability does not appear to play a role in this respondent's decision and it is not clear that an intervention is needed. Alternatively, a student may want to go to college and obtain a four-year degree, placing a 100 percent probability on enrollment. However, this student may face such a massive amount of household instability that he believes the probability of finishing after enrolling is just 40 percent, since there is a 60 percent of a degree-derailing shock. In this case, a policy intervention breaking the link between degree interruption and degree derailment could be helpful in avoiding wasted potential. Notice, however, the shortcomings of existing data: in both cases, the NLSY respondent would answer 40 percent even though the mechanism underlying the probabilities and the appropriate set of policy responses are vastly different. How do we tease out the many different contributing probabilities, just one of which is most relevant to the question at hand?

More generally, there are too many mostly unobserved uncertainties entering a subjective probability of college graduation in the period before application and enrollment decisions are made. In the model, we would like the α to represent a very specific uncertainty — that over the possibility that an adverse shock event will occur while a student is enrolled in a postsecondary program and force that student to drop out of their institution of choice. What national survey respondents believe about this particular probability and how they arrive at these beliefs remain unknown. In addition, there are of course concerns about numeracy and errors in subjective probabilities beyond basic uncertainty — this issue is clearly visible in the responses given with regard to the probability of one's own death within one year in the NLSY. In Section 2.6, we describe a survey instrument designed to alleviate these problems.

In order to reap the benefits of estimating a model like the one described above, which include assessing interventions that alter students' beliefs, the accuracy of those beliefs, or the probability that adverse shocks occur or lead to educational derailment, this survey and interview approach is a necessary tool.

2.6 Survey Instrument and Model Development

In order to address the gaps in data collection exposed above, we have designed a survey instrument which collects the following specific information, in addition to basic demographic and background information: (a) records of many types of adverse shocks similar to those in nationally representative data sets, both before and after leaving high school; (b) the level of information gathered by each individual in the postsecondary decision-making process; (c) application, admittance, and attendance history, and the rationale behind the decisions involved; (d) the nature of the individual's postsecondary education program, if applicable, and the rationale behind this choice; (e) any history of breaks, transfers, or dropping out, and the reasons for these events; (f) expectations regarding events in the individual's future, including where applicable: application to and enrollment in postsecondary schools, likelihood of completion given enrollment in different types of programs, eventual educational attainment, adverse shock events, and educational disruption due to such events; and (g) attitudes towards risk. As they pertain specifically to beliefs and adverse shocks, question types include:

- Probabilities of educational attainment outcomes;
- Expected payoffs to different educational trajectories;
- Probabilities of adverse shock events;
- Range of anticipated adverse shock events (i.e., what events students worry about).

A draft of the full survey instrument is contained in Part I of the Appendix document.

Given that concerns about uncertainties and gaps in the data are the main reasons for administering this survey, gathering responses which very specifically address these gaps is paramount. In the process of refining the survey instrument to this end, what is known as a "cognitive interview" process will be used.[21] This involves two separate but related approaches to assessing the process by which respondents answered each question. First, pilot interview subjects will be asked to communicate aloud, to an interviewer, what they understand each question to mean as they read it, as well as the thought process which leads them to the answer they eventually provide. Second, specific follow-up questions will be administered after completion of the basic survey in an attempt to address potential or apparent uncertainties. A draft of this follow-up cognitive interview is contained in Part II of the Appendix document.

An open-ended interview, in which respondents are asked to speak at length about their personal histories of shock events, their educational experiences, their decision-making processes, and their expectations for the future will also be conducted with pilot subjects. Part III of the Appendix document contains a draft of the protocol for these interviews. We view the process of gathering individuals' own stories and explanations regarding their decision-making processes as interacting, potentially iteratively, with the process of theoretically modeling these processes, so open-ended interviews may reveal the necessity of refinements to the model delineated in Section 2.5.2, which has been designed to remain agnostic as to the specific cause or causes of gaps in educational outcomes and nest expressions of the many phenomena that interviews can reveal. A crucial and novel feature of our research design is thus that while our structural model is rooted in formal economic theory,

[21] Cognitive pre-testing is often used to assess how well questions work when they are fielded, and whether they capture the scientific intent of the question. These interviews focus on whether respondents understand the survey question as well as whether they feel they are able to provide answers. This allows us to identify and improve any questions that are difficult to answer (see Desimone and Floch (2004)).

it will also be tailored to align with students' own descriptions of how they make or have made decisions. We envision the procedure as outlined thusly:

1. An economist familiar with formal models of dynamic decision-making, but unfamiliar with our specific research aims, is asked to explain in layman's terms the intuition behind the model we posit.

2. Students' own descriptions of their decision-making processes are collected in surveys and open-ended interviews.

3. An assessment is made of the similarity of the descriptions supplied by the economist and the interviewees, and if this similarity is insufficient, the model is modified in corresponding ways.

One difficulty is of course developing a method of accomplishing the comparison described in the final part of this procedure. One possible answer is to employ text similarity metrics, of which Gomaa and Fahmy (2013) provide an overview. Answers provided in the open-ended interview sessions can inform the simpler survey questions in a similar fashion as well.

In this way, the benefits of employing a variety of methods in concert in investigating our research question become clear. At the crux of this methodology is the idea that structural economic modelling represents an attempt to express the thought processes of decision-makers in a useful — systematic — way. Looked at the right way, this is rather similar to the attempt our interviewees make to express their own thought processes in open discussion with interviewers. Following the economic theory that informs the structural model to an estimable expression of the problem sheds light on what data are needed, via identification issues. Any lack in these data suggests specific requirements with regard to implementable survey questions. Moreover, the answers supplied by interviewees function as descriptions of the very mechanisms we are attempting to model, in turn revealing what may be lacking in the theory. This interplay, enhanced by the cognitive interview approach which digs deeply into the way respondents think about the subject matter, forms an iterative method of discovering potential mechanisms by which outcomes may be generated, either through theory or respondents' words, checking the one method against the other until the theoretical and social models "converge." Our belief is that, in this case, asking questions suggested by theory and reformulating the theory based on the responses will bring the economic structural model delineated above and the true process by which most individuals make decisions about education into alignment, permitting accurate and useful policy analysis on a large scale and an *a priori* basis.

2.7 Conclusions

As the decision-making process is not yet fully understood, it is not clear what specific interventions might be recommended once our data collection and analyses are complete. However, we speculate that interventions could include some combination of: information and counseling; follow-up to re-engage students who interrupt degrees due to adverse shocks; modification of full-time student requirements; modification of length of scholarships; and informing students of these changes when they are at the point of decision making. One important input in this process is the insight of community partners at institutions which deal with the kinds of students experiencing concern about adverse shocks and degree non-completion. In Baltimore, for instance, the Baltimore City Community College (BCCC) has been integral to the process of initiating surveys as well as that of conceptualizing potentially helpful interventions. This kind of institutional buy-in can be as important in the completion of projects requiring an approach like that described in this paper as are the models and estimation procedures.

This specific notion hints at the underlying purpose of this paper. Though the empirical results and structural model we present require refinement, the process by which we propose to pursue that refinement is, we believe, a novel and valuable contribution in itself. We suggest that different research modalities — the theoretical, the empirical, the qualitative, the personal — can not only *supplement* one another, stacking one kind of evidence on another, but can in fact *complement* one another, increasing the reliability and impact of the final product. Structural models of choice under constraints and qualitative interviews about individuals' experiences of such choice can symbiotically inform one another's development. In other words, the social sciences can be more than the sum of their siloed parts. It is our sincere hope that this approach can be improved upon and replicated in other contexts in which decision-making is a key subject of study.

Chapter 3

Involuntary Quits, Bargaining Power, and the Wage Effects of Labor Market Policy

3.1 Introduction

As research on the relationship between employment and housing (Desmond and Gershenson, 2016), transportation (Smart and Klein, 2015), and parenthood (Blau and Tekin, 2007; Tekin, 2007) demonstrates, the size and variability of costs and necessities associated with employment have significant ramifications for workers' outcomes. Certain strains of public policy, including public housing, transportation, and subsidization of child care, aim to remedy these issues for some workers. Assessments of the employment status effects of such policy abound, but analysis of effects on wage outcomes for the employed are more

I would like to acknowledge helpful comments from Nicholas W. Papageorge and Robert Moffitt.

scarce. In addition, as I show in my first chapter, narrowly targeted policy has the potential for economically relevant spillover effects on apparently ineligible groups in the context of statistical discrimination.

In this paper I aim to more completely answer the question of how to capture the sum total effect of labor market policies that reduce the costs of employment or their volatility. I use a variation on a model of wage bargaining in the context of job search to make predictions regarding the impact of these policies on wages for various groups of workers, and assess these predictions empirically using data from the SIPP and the example of child care subsidization. It may seem obvious that bargaining power affects the degree to which workers can capture profits from productivity increases, but esults from both theoretical and empirical analysis suggest that not only the size, but even the sign of the wage effects of employment-cost policy is dependent on the bargaining position of the worker relative to the firm. This is because, as is apparent from the model, a reduction of workers' cost of employment can generate additional surplus for both parties to a potential employment relationship. Strong firms are able to eat workers' additional surplus as well as their own, taking advantage of reduced reservation wages (the minimum value workers will accept in exchange for work). Workers with greater bargaining power, however, can leverage their increased value to firms — and how this value is increased is key — to negotiate higher wages. If both exist in a given economy, a mix of wage effects from a policy can be masked in the average and appear insignificant, as is true here.

This result is significant because it implies a compounding of worker advantages each of which can be affected by public policy. In particular, I show that union membership and concentration bear the relationship with wage outcomes predicted by the model for bargaining power, or a proxy therefor. Insofar as policy matters for union strength as well as the costs of employment, the two can be expected to have compounding effects on workers' wages. In fact, the bargaining model implies that policies affecting workers' employment stability in particular will generate a stronger interaction effect, a relevant concern when weighing the value of such interventions.

In treating unionization variables as reflecting bargaining power, I contribute to two related strands of economic literature: that concerning labor's share of income, and that reflecting the labor market impact of unions and unionization. In his overview of the former, Krueger (1999) notes that, among other purposes, factor shares of income are used to "infer the division of rents between workers and firms," as in Blanchard (1997). Of course, in analyzing or estimating a model of wage bargaining, that is precisely the division we seek to pin down. Flinn (2003) demonstrates that the demand-side data produced in the process of measuring labor's share can be used to identify the bargaining power parameter in a model of job search and matching. The author estimates that this parameter is around .4 in the U.S. economy, meaning that 40 percent of rents are captured by labor. However, Dey and Flinn (2005) suggest that for workers earning not much more than the minimum wage, this number is more like 25 percent.

The labor share literature has sought to identify the causes of a decline in the proportion of profits turned into wage income that has generally taken place across advanced economies since the 1980s. For instance, Autor et al. (2017) suggest that "superstar firms" that start with a lower labor share have captured a larger market share. Guscina (2006) finds that while the positive share effect of locational union density is marginally statistically insignificant, the effect of "employment protection" as reflected by an index, and thus the bargaining power of labor more generally, is positive and significant. Leblebicioğlu and Weinberger (2017) show that banking deregulation, and thus easy firm access to credit and bank competition, is one cause of the decrease in labor's share in the U.S., while Elsby, Hobijn, and Şahin (2013) suggest that offshoring explains a significant proportion of the change but substitution of capital for labor does not. The latter paper's results with regard to unionization are inconclusive, but the authors note that industry-specific fluctuations in labor's share of income are in fact quite common, only masked prior to the 1980s, and that the more recent decline has been led by the trade and manufacturing sectors in which unions are much more common. Meanwhile, Kristal (2013) argues that the decline of unionization in the U.S. has been a significant contributor to within-industry decreases in labor's share of income, concentrated in construction, transportation, and manufacturing,[1] and finds that union density is a significantly positive predictor of share outcomes in these industries. Results from Fichtenbaum (2011) corroborate this, suggesting that about 29 percent of the 17.9 percentage point decline in labor's share of income in the period between 1997 and 2006 can be explained by a decline in unionization.

How important are unions generally? Blanchflower and Bryson (2010) find that in the U.K., significant wage premia exist for unionized workers, particularly in the public sector, and Sojourner et al. (2015) show that in the U.S. service sector, unions have positive productivity and wage effects, but negative effects on employment. Regarding right-to-work laws,[2] Farber (2005) finds that such legislation, by impinging on union formation, may even reduce nonunion wages.

The results in this paper suggest that union membership and union concentration do have a positive effect on the share of profits individual workers receive in the form of wages, and that in fact these institutions can alter the impact of policy interventions that decrease the cost of employment by allowing workers rather than firms to claim more of the resultant common surplus. This conclusion has relevance for both policy that focuses on the relative bargaining power of workers, such as that dealing with union rules, and firms and policy that

[1] The author advances the interesting argument that the force often cited as causing firms to substitute into capital and fewer, more skilled workers — technological change — may also enhance the ability of firms to counter, circumvent, or prevent workers from building union strength.

[2] "Right-to-work" laws bar unions from negotiating contracts which condition future employment on union member status. This theoretically weakens unionization in a given state. Moore and Newman (1985) summarize the early literature on such laws, suggesting that their effects are minimal; however, Ichniowski and Zax (1991) and Ellwood and Fine (1987) suggest that unionization rates and organizing, respectively, are reduced by right-to-work legislation.

focuses on the costs of employment for workers, such as child care subsidization. A brief review of the literature regarding the employment effects of child care policy is contained in my first chapter, along with a summary of research involving job search models with bargaining of the type employed in this paper.

The remainder of this paper proceeds as follows. In Section 3.2 I exposit a model of wage bargaining adjusted to reflect the realities of separation costs for firms and instability regarding the costs of employment for workers. Empirically testable predictions result. After describing my data in Section 3.3, I examine these predictions' correspondence with reality in Section 3.4. I also assess the ability of simulations based on an estimated version of the theoretical model to produce wage change results like those described in that section. I provide concluding remarks in Section 3.5.

3.2 Model

In this section, I formulate a model of wage bargaining which accounts explicitly for the impact of demographic group separation rates on wages. The theoretical model will abstract from the contextual process of job search by workers or employee search by firms, except insofar as workers enter the negotiation process with a reservation wage presumably based in part on the value of the unemployed state, while firms know that each employee presents a risk of needing to be replaced in the future, at a cost, when a separation occurs. The bargained wage lies between the reservation wage and the firm's revenues from the match, less the wage and the expected cost of separation.

As in my first chapter, firms' inability to tell the difference between worker subgroups within gender categories will be relevant, but the emphasis will be different. Here, the key issue is that this lack of information means the reservation wage firms assume, or allow for, when deciding on a wage offer differs from the individual worker's true reservation wage.

Workers with an expected disutility of employment that is greater than the relevant gender average, such as mothers who need to fund child care, will have a higher *true* reservation wage than the reservation wage level against which firms will negotiate. Workers with a low expected disutility, such as childless women, experience the opposite. The important point, though, is that any policy which affects the quit probability or reservation wage (or both) of some subgroup of one gender will alter the wage outcomes of all workers in that gender group.

The model is based on a Nash bargaining system embedded in the classic search and matching framework. Unemployed workers match with firms at a given rate, and upon any match between a worker and a firm in this framework, a match-specific productivity level θ is revealed. The bargaining power parameter α determines how much of the match surplus, the difference between θ and the worker's reservation wage, will be offered to the worker in the form of the wage. The worker decides whether to accept such an offer and enter the employed state or to remain in the nonemployed state and continue searching. In the canonical model, there is usually a constant rate of exit from employment called the "job destruction rate," ϕ. It is at this rate that employees exogenously return to the nonemployed state.

In order to explain the empirical patterns in Section 3.4, I make four important adjustments to the essential bargaining framework used in a basic search and matching model. First, I associate a cost with separations which must be borne by firms. This cost reflects any severance or other costs of actually separating from an employee, as well as the cost of replacing the employee, including search.

Second, not all separations occur at a universal and exogenously determined rate, and the method by which some separations are generated impacts the value of employment to the worker. Specifically, workers incur a disutility cost from employment that varies over the course of the employment relationship. All workers begin any employment relationship with a disutility level c. In each period, with probability λ, an employed worker draws a new disutility level from a distribution with cumulative distribution function (CDF) F. The cost of employment represents both the psychic costs of working and the pecuniary costs, such as transportation, any materials or training not provided by the firm, and (importantly for this paper) child care. The variability of these costs represents any variability in these values for the worker — minor illnesses or injuries or a volatile workplace can cause the psychic costs of work to vary, while a vehicle breakdown or a child care arrangement suddenly falling through can bring about an increase in the pecuniary costs. When these costs increase significantly, the wage at which the individual is working may no longer be adequate to cover them. As I assume no renegotiation of wages is possible,[3] this results in the worker quitting the job and generating separation costs for the firm. The probability of a separation is therefore the probability of a quit, specified further below, plus the exogenous rate of involuntary separation ϕ.

Third, I allow the probability of a quit to vary across groups of workers by allowing the distribution from which their periodic cost draws are made to vary with group characteristics. Most significantly for this context, the probability of a costly separation ending an employment relationship is allowed to vary by demographic characteristics including gender and the presence of children. A worker from demographic group g thus enters any employment relationship with "base" disutility cost c_g and draws new cost values from distribution F_g.

Finally, I assume that firms can see workers' gender, but not their family structure. They therefore project quit probabilities based on this limited knowledge. This, plus the fact that quits negatively impact firms' bottom lines, leads to statistical discrimination in the hiring process against those in the gender group that includes the most quit-prone

[3]This assumption particularly makes a good deal of sense at the low end of the wage distribution, in occupations on the front lines in retail and other service industries. Ransom and Oaxaca (2010) find that women in these occupations, in particular, have a low quit-rate elasticity with respect to wages.

workers. The more quit-prone gender group in the data used in this paper as well as in general is women, and the quit-prone subgroup largely driving this gender gap is mothers of young children. This assumption also creates the potential for spillover effects from any policy that impacts a specific gender subgroup based on family structure, such as child care subsidization. It generates the gap discussed above between the reservation wage levels of workers who appear identical to firms. For example, if mothers (women with kids, group fk) frequently incur a greater (psychic and pecuniary) cost of employment than childless women (group fn) due to child care costs, their initial c_{fk} would be greater. And because child care arrangements are potentially volatile, the distribution from which mothers draw new cost values, F_{fk}, would have a greater variance in addition to a larger mean.

In combination, as I demonstrate in Section 3.2.1, these features mean that the model's prediction concerning the relationship between wage offers and a change in quit rates is ambiguous. In particular, a change in quit rates resulting from a decrease in the cost or cost variance of employment will have opposing effects on the wage negotiation, decreasing the expected cost of the employment relationship for *both* the firm and the worker. The sign of the resultant change in the wage will in large part be determined by bargaining power: if workers' bargaining power is great, they enjoy most of the surplus generated by a longer employment relationship, but if that power is small, firms may be able to seize all these profits and in fact lower wages because workers are happier with their more stable, lower-cost labor market experience. Childless women's reservation wages are not affected by the policy directly. However, since their search prospects will change based on the wages on offer, the value of the unemployed state will be altered for them, in turn generating a change in their reservation wages. In fact, if women's wages rise (resp. decline) overall, this implies a larger (resp. smaller) reservation wage for childless women, reinforcing the effect on the average outcome. However, this change will be secondary relative to the change in mothers' reservation wages. The most important thing to hold in mind is that, due to firms' inability to distinguish women at a high risk of quitting from those at a low risk, a policy that alters the quit-proneness of only the high-risk group will affect wage offers to all female job applicants identically.

3.2.1 Specification

In the employment state, individual i pays a flow utility cost c_{it}, where t is the number of periods since being hired; for workers in group g, $c_{i0} = c_g$. New employment disutility levels are randomly drawn at frequency λ from a group-specific distribution $F_g(c)$ which has support $C = [c_g, \infty)$, and the cost remains at the drawn value until a new draw is taken. Fluctuations in c_{it} explain quit behavior because if a high employment cost value is drawn, the present discounted value (PDV) of employment to the worker decreases, and may decrease enough to alter the worker's decision with regard to their current employment arrangement. A critical cost value depending on the wage, $c_g^*(w)$, will therefore exist on each job above which the worker will quit, and the probability of drawing a quit-inducing cost value will be $1 - F\left(c_g^*(w)\right)$. When a new draw of c_{it} induces a quit by a worker or an exogenous demand-side separation occurs, firms pay a cost c^F.

Denote the value of the nonemployment state for a group-g worker by V_g^N. After rearranging terms in a Bellman equation expression, the value of the employment state at wage w to the worker at the time of wage negotiation can be expressed as

$$V_g^E(w, c_g) = \left(\rho + \phi + \lambda\left(1 - F\left(c_g^*(w)\right)\right)\right)^{-1} \times \left(w - c_g + \lambda\left[\int_{c_g}^{c_g^*(w)} V_g^E(w, c)\, dF_g(c) + \int_{c_g^*(w)}^{\infty} V_g^N dF_g(c)\right]\right), \quad (3.1)$$

where individuals and firms discount the future at shared rate $(1+\rho)^{-1}$ and $c_g^*(w)$ is the critical disutility value generated by the prescribed wage. While employed, the worker earns the wage w and pays the cost of employment c_g, but also anticipates new draws from F_g which will either alter the continuation value of the employed state if below c_g^* or cause a return to V_g^N if above that critical value.

The value of a group g worker to a firm in a match with productivity value θ is

$$V_g^F(\theta, w) = \left(\rho + \phi + \lambda\left(1 - F\left(c_g^*(w)\right)\right)\right)^{-1}\left(\theta - w - \lambda\left(1 - F_g^*(\theta, \phi) + \phi\right)c^F\right). \tag{3.2}$$

Each period, then, the firm reaps θ in revenue but pays out wage w and is at risk of paying the separation cost.

The Nash bargaining wage function is expressed

$$w_g(\theta) = \arg\max_w \left\{\left(V_g^E - V_g^N\right)^{\alpha}\left(V_g^F\right)^{1-\alpha}\right\}. \tag{3.3}$$

I assume that if there is no wage for which both $\left(V_g^E - V_g^N\right)$ and V_g^F are positive, no offer occurs. If I additionally assume that the firm knows each worker's group g and thus their initial cost and cost distribution, it is possible to show that the wage resulting from a Nash bargaining process will be

$$\begin{aligned} w_g(\theta) = &\left[\alpha\left(\frac{dV_g^E}{dw}\right) - (1-\alpha)\left(\frac{dV_g^F}{dw}\right)\right]^{-1} \times \\ &\left[\alpha\left(\frac{dV_g^E}{dw}\right)\left(\theta - \left(\lambda\left(1 - F\left(c_g^*(w)\right)\right) + \phi\right)c^F\right) - \right. \\ &\left.(1-\alpha)\left(\frac{dV_g^F}{dw}\right)\left(c_g + \rho V_g^N - \int_{c_g}^{c^*}\left(V_g^E(w, c) - V_g^E(w, c_g)\right)dF(c)\right)\right]. \end{aligned} \tag{3.4}$$

If quit rates were constant with respect to the wage, the derivatives of the value functions for the employee and the firm would be equal to one and negative one respectively, and the complex quit probability expression could be replaced by a constant. However, in the present case, an increase in the wage does not only transfer instantaneous flow value from the firm to the worker; a wage increase also reduces the probability that a future cost draw will induce a quit, increasing the expected duration of the match and conferring some additional value on both parties. Firms therefore have some incentive to offer a wage that is higher than would otherwise be optimal in order to keep quit-prone workers on the job.

This significantly complicates analysis, and it seems reasonable to expect that the effect (or firms' reactivity to it) would be relatively small and in any case tend to inflate any relationship between wages and quit rates otherwise implied by the model. So, I suppose that c^* depends not on the wage, but instead on θ — workers are still less likely to quit high-productivity jobs, but firms cannot influence their propensity to quit by offering a higher wage than is otherwise justified. In this case, c^* is taken as a constant for any specific job and the derivative terms simplify as noted above, resulting in the following wage expression:

$$w = \alpha \left[\theta - \left(\phi + \lambda \left(1 - F\left(c^*\right)\right)\right) c^F\right] + \\ (1-\alpha)\left[c_g + \rho V_g^N - \lambda F\left(c^*\right)\left(\rho + \phi + \lambda\right)^{-1}\left(c_g - \mathbf{E}\left[c | c \le c^*\right]\right)\right]. \quad (3.5)$$

Note that if firms expect too high a c_g or F_g, there may be no offer made where one could in fact be mutually beneficial. If firms' expectation of F_g is too low, they may make a losing offer, since the worker is more likely to quit than expected; on the other hand, if their expectation of c_g is too low, they may make an offer that the worker will refuse, since their belief about the negotiating floor is wrong. Incorrect expectations regarding these factors are precisely the result of the limited information case described previously, in which women with and without children look identical to firms.

Within gender groups, family structure subgroups with greater expected flow disutility from employment will have a smaller V_g^E and a larger quit rate at any wage level than firms project, while subgroups with smaller expected disutility experience the opposite. The direction of the net effect of these misalignments — the effect of statistical discrimination — on wages is theoretically ambiguous. In most applications of statistical discrimination theory, it is assumed that firms are discriminating on differing productivity, so that the direction of the predicted wage effect is obvious. Here, however, the differentiating characteristic, proneness to quits due to family instability, also impacts workers' reservation wages — a more likely quitter must also be paid more in order to agree to work in the first place, since the higher potential disutility of employment is what generates more frequent quits. Thus, firms may statistically discriminate without having a discernable effect on wages in particular, as Section 3.4 suggests that, on average, they do.

In Section 3.2.2, I show that the sign of the relationship between quit probabilities and wages depends on α. Intuitively, this result owes to the fact that, in this model, increased quit rates harm both parties to an employment relationship in a unique way — quits are not merely productivity concerns, but represent an imposed cost for firms as well as the loss of an income stream to workers and a return to the unemployed state. While the voluntary decision to quit might typically be thought of as necessarily utility-maximizing, this picture is muddied when the workers under consideration are those on whom policies like child care subsidies ought to have the greatest effect in terms of reducing quits. Such workers would likely prefer to work *but for* a pressing family concern. Greater c_g and F_g do not only represent an increase in the quit rate, but also an increase in the expected disutility of the employed state. After such an increase, then, the surplus available in the employment relationship is squeezed out from both sides — firms are more likely to lose a worker and pay a quit cost, so they see a reduced expected profit, and workers are more likely to experience hardship, so they increase their reservation wages. If the bargaining power of firms is extremely great, though, the wages they offer are already quite close to the reservation wage, which is the negotiating floor. If this floor is raised by increased employment disutility, firms may need to increase these offers simply to hire workers at all (on what would still be, for the firms, relatively lucrative contracts).

3.2.2 Wage Determination and α

What determines whether an "increase" in F_g, and the attendant increase in quit probability, drives group wages down? I will define such an increase as a shift to a new disutility distribution which is first-order stochastically dominant (FOSD) to the original. In the event of this increase, then, $F_g\left(c_g^*(w)\right)$ is reduced for all w — that is, quit probabilities increase for all jobs, in addition to the increase in the expected cost draw. Assume that any change in F_g shifts c_g in the same direction — an increase in quit probabilities comes with an attendant increase in the base cost of employment.[4] If we (somewhat informally) take the functional derivative of the wage in Equation 3.5 with respect to F_g, expressing the operation as $\frac{d}{dF_g}$, it reduces to

$$\frac{dw}{dF_g} = \alpha\lambda c^F\left(\frac{dF(c^*)}{dF_g}\right) + (1-\alpha)\left[\frac{dc_g}{dF_g} + \rho\frac{dV_g^N}{dF_g}\right.$$

$$\left.+\lambda(\rho+\phi+\lambda)^{-1}\left[F(c^*)\left(\frac{d\left(c_g - \mathbf{E}\left[c|c\leq c^*\right]\right)}{dF_g}\right) - \left(\frac{dF(c^*)}{dF_g}\right)\left(c_g - \mathbf{E}\left[c|c\leq c^*\right]\right)\right]\right]. \quad (3.6)$$

If and only if this expression is negative does a FOSD shift of F_g reduce wages. However, its sign is ambiguous and depends in a significant way on the bargaining power parameter.

[4]This need not be true in theory, obviously, but it makes sense as applied to the scenarios concerning child care or transportation costs.

The relevant uncertainties become clearer upon examination of the individual terms in this expression.

The first summand is assuredly negative. The parameters $\{\alpha, \lambda, c^F\}$ are all necessarily greater than zero, meaning that the sign is that of the derivative term. This derivative is negative due to the FOSD shift assumption. Thus, in the extreme case in which $\alpha = 1$ and workers own all the bargaining power, wages will fall when quit probabilities increase. Workers receive all the profit from the employment contract, but increased quits eat into that profit (in expectation) by generating greater turnover costs for the firm. This is the expected result.

However, consider the second summand, the bracketed term multiplied by the firm's bargaining strength $(1-\alpha)$. The first term inside the large brackets is positive by assumption, while it is clear that the second term, the derivative of the value of the nonemployment state with respect to F_g, is negative because the value of that state is derived entirely from the potential for employment draws, all of which decrease in value when employment costs increase. Thus, ambiguity in the sign of the second summand is already present.

Focusing on the remaining values, the sign of the first term in the small brackets depends on how the difference between the base cost c_g and the expected contract-life cost change with F_g. Intuitively, we expect that an increase in F_g ought to increase the expected value of a new cost draw on the job, meaning that this term would be negative. It should be noted, though, that this is ambiguous, and not just because c_g increases by assumption. Some portion of the distribution F_g is being pushed *beyond* c^*, into the quit zone, where the outcome is just the unemployed state. Only the potential for increased costs that do not induce quits is of concern here. If previously the individual could expect frequent draws of employment cost that would make continuing to work difficult, but not impossible — increase costs near the critical point, but not past it — then the worker would have a relatively high expected on-the-job cost value, and not anticipate taking home much profit. If a shift of F_g

pushes these high probabilities to cost draws just beyond the critical value then, *provided the worker continues on the job*, the expected cost value may decrease.[5] Moreover, because the sign of the second term in small brackets is necessarily negative, the difference of these two terms amounts to subtracting a negative value from a value of ambiguous sign. It is thus quite likely that this difference is positive.

Now, consider the extreme case in which $\alpha = 0$ and firms own all the bargaining power. As I have just described, there is a good deal of uncertainty about the sign of the effect of an increase in quit rates on the wage. In particular, it is more likely to be positive if there is a large change in the base cost of employment, c_g, or if expected *on-the-job* costs of employment are larger — in essence, if not only are quits more likely, but employment itself is in general more burdensome. If firms are very strong in wage negotiations, an increase in the cost of employment for workers translates into higher wage offers that offset this cost. This is because firms are reaping all the available profit, and are willing to cover the necessary costs for workers in order to hire them. Of course, any jobs on which the match productivity falls between the initial c_g and the new, larger value will now make no offer at all, so hiring rates are lower. Average wages for the whole group of workers may thus go up or down, since they will more often be making no wage at all. However, among the employed, wages rise.

This of course implies the opposite reaction as well: in the strong-firm scenario, a decrease in F_g and c_g could well lead to decreased wages. Workers may still be better off, because some of the new surplus is generated in the form of lengthier employment relationships, fewer spells of nonemployment, and lower disutility during employment. But measured wages can fall, because firms see the decrease in their employees' costs, and claw most of this benefit back in the form of lower wages. The bargaining power parameter

[5] This may require a bimodal cost distribution. However, such a distribution is reasonable in the cases of interest; sudden new vehicle repair expenses or child care issues represent potentially large discrete jumps in employment costs, which suggests a distribution of potential cost draws in which some concentration are quite low, essentially the same as the starting value, but another concentration are rather high.

α thus plays a significant role in wage outcomes after changes in quit rates, particularly after changes in policies that affect the variable cost of employment. If workers are strong, decreases in costs and quits unambiguously increase wages. But if firms have the bargaining power, this outcome is ambiguous and wage increases seem unlikely.

The foregoing analysis implicitly assumes that the changes in F_g being discussed are fully visible to hiring firms — they represent shifts in, for instance, the gender-wide disutility distribution the firm observes. Since all the value terms ($V_g^{\cdot}$) in the wage expressions are generated based on firm knowledge, the effect on individuals in group g of a shift in F_g will be reduced to the effect achieved by the resultant shift in the overall gender distribution known to firms. On the other hand, individuals outside group g in the same gender group will experience exactly the same shift in wage offers, despite there being no change in their distribution of disutility or true quit probability — for instance, single childless women in this model would be forced to bargain based on much higher costs and quit probabilities as a part of their entire gender group than they would if their full family structure could be known and they were not forced to pool with the entire gender group. The effect on their wage offers is of course ambiguous and dependent on α as well. We therefore cannot predict the wage effects of a policy that alters a group's (or subgroup's) propensity to quit, such as child care subsidization. I explore this implication empirically in Section 3.4, after discussing the data I use to do so in Section 3.3.

Before proceeding, however, I note that similar types of predictions would look quite different with the assumptions under which group differences and discrimination are typically analyzed, that a difference in *productivity* (perceived or real) drives outcome gaps.[6] In this case, all the added complexity above falls away, and differences in θ drive wage gaps. Since the derivative of the wage with respect to θ is simply α, a smaller productivity value of

[6]See Fang and Moro (2011) for a summary of research regarding statistical discrimination, and in particular the example of Sattinger (1998) which deals explicitly with quit probability but treats it abstractly as a component of the present discounted value of workers to firms.

course results in a lower wage regardless of bargaining power — only the magnitude of that difference in fact depends on the power balance. If such a model were true, policy which reduces "unproductive" quits ought never to decrease wages. However, as I show in Section 3.4, the data suggest that in some contexts one such policy does just that. The model in this section provides an explanation for this outcome.

3.3 Data

I employ data from the 2001 and 2004 panels of the Survey of Income and Program Participation (SIPP). I restrict the working sample to individuals who at all points in the sample are between the ages of 25 and 55. Individuals who report significant self-employment income in any period are removed as well,[7] along with individuals who ever fail to provide interview responses in a particular wave.[8] Finally, I include in the analytical sample only those individuals who have no bachelor's degree, in order to focus on those workers for whom policy regarding employment stability is most likely to be relevant. This leaves me with 48,216 individuals, each observed in about 29 months on average.

Importantly, the SIPP includes information on whether individuals received public child care assistance, the specific cause of any job separation[9], and the union status of any employed individual. I thus define the most important analytic variables as follows.

Child Care Subsidies. The key policy variable in this paper is child care subsidy levels. As in my first chapter, I use the maximum subsidy payout per week to reflect each state's

[7]Employment statuses are inconsistently reported in the SIPP alongside self-generated income. This creates an issue for recording and measuring employment spell durations. Removing such individuals results in a reduction of the sample size of less than 5 percent.

[8]Non-interview waves in the SIPP are filled in with imputed data, which generates a relatively large number potentially spurious employment status transitions. Eliminating these respondents reduces the sample size by 13 percent.

[9]This is provided an answer to this question is recorded; around half of transitions from employment to nonemployment have no cause specified.

generosity with regard to subsidies.[10] I extract child care assistance payment maxima for state-year pairs from biannual reports produced by the National Child Care Information Center of state plans for their use of Child Care and Development Fund dollars. Because these plans were submitted biannually, states' child care subsidy maxima are set at constant values for two-year periods. Figure 9 shows the trajectories of child care subsidy policy by state over the eight-year course of the two SIPP panels. It demonstrates that there is meaningful variation in maximum subsidy levels both among states in each year and within many states over time. For use in reduced-form estimation, I standardize the subsidy maximum variable so that coefficients represent the effect of a one-standard-deviation increase in the maximum subsidy value.

Occupational Groups. I control for occupation throughout this paper, primarily using a simplified structure which includes four job categories constructed so that the educational requirements and wage outcomes of their constituent occupations, as evidenced by the SIPP data, are relatively similar: high-end, mid-tier, and low-end services, and manual work. High-end services include management, STEM occupations, and sales of financial services and large durables like homes and vehicles (i.e., non-retail items). Mid-tier services covers personal and health services and clerical work. Low-end services include hospitality, food service, and retail, while manual occupations include trades like construction and manufacturing as well as mechanics and transportation. These parsimonious groupings suffice to control for any relevant occupational effects and reverting to the larger set of controls does not alter my results.

Group Quits. The group quit rate I assume firms use to negotiate is calculated for groups of employed workers defined by their gender, age (younger than 40 or not), occupational

[10]See my first chapter for further discussion of child care subsidy policy.

group, and region, within the year in which the observation takes place. The rate is simply the number of quits that occur each year in each group thus defined divided by the number of months spent employed by workers in the group, multiplied by 100. The events which count toward the rate include quits due to working conditions, departures for new jobs, illnesses and injuries, departures for familial obligations or school or retirement[11], and voluntary quits for "other" reasons.

Contextual Union Concentration. Even in the simple canonical model of job search, worker bargaining power is notoriously difficult to identify with supply-side information alone. Since in this context I am interested in bargaining power that differs by group, the question is even thornier. Demand-side data can be used to identify the bargaining parameter α in a broad sense, but the SIPP does not contain such data. One intuitive proxy for worker bargaining power, however, is union membership — we expect that union jobs come with more negotiating strength on the worker side. The issue is that union membership is of course endogenous to wages. Thus I construct a variable reflecting the prevalence of unions in the demographic groups relevant to each worker, which I will call "contextual union concentration." I define the groups as in the construction of group quit rates above, and calculate a unionization rate for these groups in the same way as the quit rate: I divide the number of months in which group workers report employed union membership by the total number of months spent employed by group workers and multiply by 100. I exclude each individual's unionization status from the calculation of their contextual union concentration in order to avoid endogeneity concerns, as I note in Section 3.4.1.

Summary statistics for key variables can be found in Table 37. Among the employed, male wages are on average \$3.34 higher than female wages, a 25 percent difference over the female average. Meanwhile, quit rates are larger for women, occurring in 0.37 percent of

[11]Retirement and departures for school are quite rare due to age restrictions placed on the sample.

their employed months as compared with 0.24 percent for men, a 35 percent difference. Men are also much more likely to be unionized, at a 19 percent rate rather than the 10 percent rate for women. This is of course likely related to the occupations in which these workers are employed. This is why contextual union concentration is calculated within, rather than across, broad job categories.

3.4 Union Concentration and Wage Outcomes

In this section I assess the relationship of wages to group quit rates, the impact of employment stability policy on wages via this relationship, and the mediation of all of the above by bargaining power. If quits are simply a productivity concern for firms, we may expect that an increase in bargaining power would inflate the benefits of stability policy for workers, as in the model above. However, we would also expect to find that reducing quits has a universally positive relationship with wage outcomes. But if quits are generated by changes in the the cost of employment, there is potentially a more complex relationship between quit rates and wages. In particular, if results demonstrate that the effect of reducing quit probabilities can have a negative effect on wages in certain contexts, it would rule out the productivity model, but the evidence would be compatible with the model described in Section 3.2.

The operative example of employment stability policy is child care subsidization. As noted, there are low income caps on eligibility for such subsidies in the United States. I thus restrict my sample to those individuals with less than a bachelor's degree in order to focus on those workers more likely to potentially be impacted by subsidy policy.

3.4.1 Empirical Approach

To examine the model predictions outlined above, I estimate a linear regression model of the log wage:

$$ln\left(w_{i\tau}\right) = \beta_0 + \beta_u\left(UC_{i\tau}\right) + \beta_{cc}\left(CC_{i\tau}\right) + \beta_{int}\left(UC \times CC\right)_{i\tau} + \beta_X X_{i\tau} + \varepsilon_{i\tau}, \tag{3.7}$$

where $UC_{i\tau}$ is the union concentration in worker i's group, $CC_{i\tau}$ the standardized weekly child care subsidy maximum in worker i's state at time τ, and τ is used to denote the period within the panel (since t represents time in the current spell in the theoretical model). As covariates in the vector $X_{i\tau}$, I include race and ethnicity (dummies for black, non-white non-black Hispanic, and other non-white), marital and disability status, education (whether the individual has a high school diploma or attended some college), age and its square, other state-level policy variables (worker's compensation generosity, unemployment insurance benefit maximum, and minimum wage), and fixed effects for year, state of residence, and occupation. I treat each person-month as an observation and thus cluster standard errors at the individual level.

I first estimate Equation 3.7 *without* the interaction term in order to establish the estimated effect of the quit-reduction policy on wage outcomes across contexts for the full sample as well as male and female subsamples. I then introduce the interaction term. The coefficient β_{int} captures the way the wage effect of subsidy policy changes with the unionization context. If it is positive, then as union membership becomes more prevalent within one's gender, age, area, and occupation groups, the wage impact of child care subsidies becomes more positive. This would be a valuable result in itself, but would not distinguish the model in Section 3.2 from a basic productivity model of the subsidy's effects. However, if in a low-union-concentration context the estimates suggest that the wage effect of child care subsidies would be *negative*, the result would contradict the productivity model and support the inclusion of a nuanced structure for the value of the quit probability.

It is worth discussing the use of a "worker group union concentration" variable, rather than an indicator of each worker's own current or eventual union status. The latter is of course endogenous with respect to the wage — union formation tends to occur in low-wage occupations and amongst those who make lower wages within broad occupational categories, and the concentration of union workers in specific worker groups may well be linked to (lobbying for) policy efforts on that group's behalf. All these connections muddle any relationships to be estimated among wages, unions, and policy effects. In addition, it is possible and maybe even likely that union presence in contextually relevant jobs — those held by workers with the same characteristics in the same broad occupational category — enhances the outside option for workers, increasing their reservation wages and thus their negotiating position. For these reasons, group union concentration makes the most sense as a proxy for worker bargaining power.

However, I also apply a 2SLS approach in which individual union status and its interaction with child care subsidization are endogenous variables instrumented by the union concentration variable and its interaction with child care subsidization. That is, I estimate a model of the form:

$$ln\left(w_{i\tau}\right) = \beta_0^{IV} + \beta_u^{IV}\left(U_{i\tau}\right) + \beta_{cc}^{IV}\left(CC_{i\tau}\right) + \beta_{int}^{IV}\left(U \times CC\right)_{i\tau} + \beta_X^{IV} X_{i\tau} + \varepsilon_{i\tau}^{IV}; \quad (3.8)$$

$$U_{i\tau} = \gamma_0 + \gamma_u\left(UC_{i\tau}\right) + \gamma_{cc}\left(CC_{i\tau}\right) + \gamma_{int}\left(UC \times CC\right)_{i\tau} + \gamma_X X_{i\tau} + \nu_{i\tau}; \quad (3.9)$$

$$\left(U \times CC\right)_{i\tau} = \delta_0 + \delta_u\left(UC_{i\tau}\right) + \delta_{cc}\left(CC_{i\tau}\right) + \delta_{int}\left(UC \times CC\right)_{i\tau} + \delta_X X_{i\tau} + \eta_{i\tau}, \quad (3.10)$$

where $U_{i\tau}$ is a dummy indicating the worker's own union status and the X vector contains all the same covariates as in Equation 3.7.

In order for such a model to be viable, certain things must be true. It is reasonable to suppose that union concentration in one's state, occupation, and gender group will significantly influence one's own union status, and results in Section 3.4.2 corroborate this. I must also assume that all the variables in the second and third equations above are exogenous with respect to the associated error terms. But of course, an individual's own union status contributes directly to the basic calculation of contextual union concentration described above. Therefore, in this IV context, I use contextual union concentration as calculated from all individuals in the group other than individual i. Finally, if I want the estimated coefficient on $Union_{i\tau}$ to represent the true relationship between union status itself and the wage, I must assume that union concentration influences individuals' wage only through its effect on the probability that each worker is a union member. My suggestion above that contextually relevant union concentration might increase the wages of nonmembers appears to contradict this, and imply that I will arrive at overestimates. However, remember that union status is here not the true variable of interest, but a proxy for that variable, bargaining power; the degree to which union concentration enhances bargaining power in other ways is in fact part of what I hope to capture. However, I interpret the 2SLS results with caution, and merely as a check on the basic estimates.

3.4.2 Results

The central estimation results are reported in Table 38. Gender and union status have a statistically significant effect on wage outcomes, with men and union members receiving higher wages by a margin of around 25 percent in each case. The effect of the worker's own union membership on the final wage is smaller for women than for men, but still significant. However, the estimated coefficient on child care subsidization is not only statistically insignificant, but negative.[12] If we want to believe that child care subsidies positively affect

[12]In results not reported here, I estimate that this is true even for recipients of subsidies, whether by restricting the sample to this group or by interacting the subsidy generosity effect with a dummy indicating

the productivity or labor market attachment (and thus the value to firms) of any workers, these are worrisome results.

The introduction of contextual union concentration reveals a nuanced story within the estimates. There are no effects for men of child care subsidies or their interaction with union concentration, as expected. Yet estimates suggest that without any union power, increases in child care subsidy maxima (and therefore reductions in female quit rates) would in fact significantly *reduce* wages for women. In such a case a one-standard-deviation increase in the subsidy maximum is estimated to reduce wages paid to *all female workers* by about two percent, which translates to around a quarter per hour, or $500 per full-time year, for the average worker in this group. In this case, firms are able to capture an outsized share of the surplus generated by reduced quits, while workers may still be better off due to the increase in the stability of their home and work lives. Another way to describe this would be as a reduction in the costs of work to potential laborers, of which firms take advantage.[13] However, with each percentage point increase in unionization, the wage-enhancing power of child care subsidies rises in a statistically significant way. At under 18 percent unionization, which is around the 80th percentile for state-year observations among women, subsidization begins to raise wages.

Table 39 reports estimates from the instrumental variables model. In the first stage for all workers, an increase of one percentage point in contextual union concentration is estimated to increase the probability that an individual worker is in a union by nearly one percentage point.[14] F-test scores for this instrument suggest that, though it may be weaker for female workers than for male, it is strong enough to provide good estimates in the second

receipt.

[13]It is thus possible that *net* wage offers rise, since child care costs are not being taken out of each paycheck at the same rate. However, measured wages, and payroll costs to firms, decline.

[14]Recall that the individual is excluded from the calculation of contextual union concentration, so this is result does not owe to a mechanical correlation. If the individual is left in the relevant concentration calculation, the coefficient on this variable in the first stage increases by approximately one tenth of a percentage point.

stage in each group. The second-stage estimates corroborate the qualitative story told by the OLS results: child care policy has no wage effects for men, but for women who are not union members an expansion of child care subsidization reduces wages. Again, the estimate suggests that a one-standard-deviation increase in subsidy maxima will drag women's wages down by 2 percent. However, for female union members, the effect is quite the opposite. These workers can expect a wage increase of about 13 percent all told with a similar increase in child care subsidy generosity. All these effects are statistically significant at no less than the 10 percent level, and the difference in wage adjustment by union status is significant at the 1 percent level.

Thus, the empirical evidence corroborates the model described in Section 3.2. Moreover, it suggests that the final effects of many labor market policies, but certainly and in particular those designed to increase labor market attachment by reducing the costs of work, depend quite strongly on the bargaining atmosphere in which individuals search for work and firms hire. Worker bargaining power in the form of union membership and union concentration can translate the impact of policies having little to do with unions themselves into more beneficial outcomes for workers.

3.4.3 Search Model Re-estimation and Simulation

In this section I use the estimates generated by the search model in my first chapter to simulate wage outcomes for workers in different child care subsidy environments under the assumption of various values of the bargaining parameter α. In order to perform these simulations I must first re-estimate the parameters of the productivity distribution $G(\theta)$ for each group given the new assumed value of α.[15] For example, under the assumption that $\alpha = 1$, the productivity distribution that explains the wage outcomes in the data will be

[15] In the original estimation, α is fixed at 0.3.

essentially the same as the distribution of wages itself, because workers are capturing all surplus in the form of their wages. But under the assumption that $\alpha = .2$, the productivity distribution that explains the true wage outcomes will be concentrated at much higher values, since firms retain a large proportion of total productivity and a small fraction is translated into wages. By re-estimating the distributions, I prevent changes in α from generating absurdly low or high wages in simulation. I fix all parameters of the model other than the parameters characterizing the lognormal productivity distributions at the values estimated in my first chapter, and re-estimate the model using a maximum likelihood procedure otherwise identical to the one in that paper to determine the productivity distribution parameters.

Once this re-estimation has been performed, I use the new distributions and the other retained parameters to simulate 25,000 individuals just as in my first chapter, under new assumptions about the wage generating process. In particular, I add to firms' calculation of workers' reservation wage a cost of child care that can be reduced by subsidies. Child care subsidies still reduce quit rates as in the original simulations, but now also reduce reservation wages by reducing the cost of employment. Firms add to women's reservation wages a child care cost equal to the average subsidy available in the data at a per hour rate, about \$3, multiplied by the fraction of female workers who actually use some form of child care, about 0.21. They subtract from this the child care subsidy value applicable in their state multiplied by the fraction of eligible female workers who access those subsidies, about 0.12, up to the average available subsidy (so that even where subsidies are more generous than average, this difference is never less than zero — firms don't expect subsidies to provide more than the full cost of child care to recipients). Child care costs thus add to firms' estimation of women's reservation wages in two ways: some proportion of women have children but do not access subsidies, so firms assume they pay for care, but there is also an often significant difference between the supposed cost of child care and the available subsidy, leaving a gap that must be covered by the worker. In this way, large child care subsidies both reduce quits for recipients, making female workers appear more valuable to firms, and reduce employees' costs, making work more valuable on net to workers.

I assume for simplicity that there is only one exogenous layoff rate ϕ on the job market. In order to demonstrate the effect — specifically the wage gain that results from the implementation of more generous subsidies — at a reasonable magnitude, I must also assume for simulation that the cost of a separation to the firm is on the order of \$80k. This is around one order of magnitude larger than the typical separation cost described in the management literature, though there are some types of recruiting that according to that literature do cost tens of thousands of dollars. I hypothesize that the main reason for this is that the model does not account for the demand-side possibility of retaining a vacancy and waiting for another applicant. In the model, firms choose between making a productive match or getting zero return, but on the true job market, firms have the option to pay a possibly quite low vacancy cost and continue searching — many vacancies are not even filled until multiple candidates have been interviewed. Thus, in order to justify a wage offer in reality, firms must view the applicant as more desirable than the likely outcome of continued recruiting efforts (less any vacancy costs), not merely more desirable than no production at all as in the model. One key extension to the model, then, is a general equilibrium framework in which firms can weigh these options and make wage offers accordingly. In such a context, a much smaller cost of separation may justify a larger decrease in the wage offer, since a similarly productive and less quit-prone worker may be right around the corner.

Given these assumptions, I plot in Figure 10 the difference between average wage offers received by simulated white women under 40 with a high school education in two scenarios: all available child care subsidies are set to the maximum level available in any state in the data (\$275 per week), and all subsidies are set to \$0. The x-axis reflects (ten times) the parameter α, or workers' bargaining power.[16] That is, at each value of α at one-tenth intervals, I subtract the simulated average wage for women in the no-subsidy scenario from the simulated average wage for women in the maximum-subsidy scenario, then divide this difference by the no-subsidy average wage to arrive at a percent change. According to Figure 10, for low levels of bargaining power workers' wages do not merely remain stagnant, but in fact *fall*, in the face of generous child care subsidies. With $\alpha = 0.1$, this decrease is just over 2 percent — about the level of wage decrease found in the data for nonunion women with a one-standard-deviation increase in child care subsidy generosity. However, when workers have more bargaining power, they are benefitted by the reduction in female quit rates generated by the introduction of subsidies. At a very high level of worker bargaining power, $\alpha = .9$, the increase in subsidy generosity boosts wages for workers by over 5 percent. Thus, a model of job search and bargaining with the right specification can produce results on the order of those suggested by the data.

3.5 Conclusions

In this paper, I have demonstrated using a model of wage bargaining that policies which reduce the cost of employment as well as the volatility of that cost for workers can have widely varying effects on those workers' wage outcomes depending on their power in the bargaining process. Of particular importance is the prediction that wages could fall if workers have particularly little power — that the cost savings that allow burdened workers to afford employment could be in part captured by firms who can negotiate those workers down to their

[16] I plot the difference between the two scenarios because, due to the re-estimation process, average simulated wages decrease as α increases. This does *not* imply that more worker bargaining power drives wages down; rather it simply indicates that a search model estimated on the *assumption* that α is larger will reflect a productivity distribution with a much smaller right tail in the simulation process, leading to slightly lower average simulated wage outcomes. A graph of the raw predicted averages, though, may give the false impression that increased bargaining power would be detrimental for a *given* productivity distribution, which is not what is depicted in Figure 10.

reservation wages. I have also provided empirical evidence that this theoretical prediction is borne out in the wage response to child care subsidies. Female workers, treated as a homogenous group by firms, see lower wages where subsidies are more generous unless they have the bargaining power enhancement of union membership, which in fact generates wage increases for women in otherwise identical contexts.

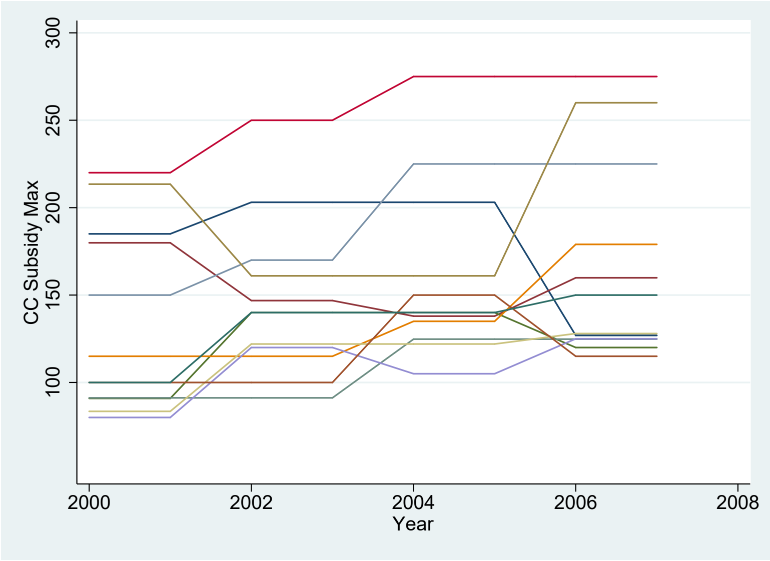
If the goal of policies like child care subsidization is to "make work pay" for workers with costs that attend employment, it would seem that a resultant wage offer reduction for those same workers in response to the policy counteracts that goal. In essence, some proportion of an in-kind benefit for employees is being transferred to employers, who are aware that this benefit reduces the basic wage a worker in a certain group requires — despite the fact that in general such a benefit also increases workers' value to firms in terms of expected profits, whether by reducing quits or enhancing productivity. In fact, in a context of statistical discrimination, many workers who were previously unaffected by the relevant cost of employment may see their wages decline because their employers are no longer concerned that *any* employee will *ever* need to cover such a cost.

However, this is only a relevant concern in employment relationships in which firms have the power to pay their employees something close to the bare minimum wage that they require in order to make working worthwhile. Policy that enhances workers' ability to bargain can shift the incidence of the benefit of *all* complementary labor market policies. In the end, this may seem an obvious point. However, it is important to hold it in mind when assessing the effects of other labor market policies; any results with regard to the worker-income effects of a certain labor market policy may hide divergent outcomes for workers having bargaining power and workers lacking it. Disregarding union concentration or membership, I estimate that child care subsidies have no effect on wages. But this conclusion disguises that such subsidies may well impact wages in counterbalancing ways for workers in contexts that vary across location and time. This is an important caveat in assessing the effects of specific labor market policies, but also in designing a full suite of such policies.

Additional research could assess the applicability of the model and empirical approach in this paper to other policies addressing the costs of employment, including housing and transportation. Refining the use of the search-and-bargaining model in similar contexts to assess the impact of unionization and other bargaining-power shifters on the impact of labor market policy is an important avenue for future research. It may be possible to use demand-side data to identify the bargaining power of workers in industry- and union-status-specific contexts. On the other hand, it appears it may also be possible to calibrate such a model to predict the wage outcome changes revealed in the data, providing a different estimate of the parameter α. This would of course impose the assumption that bargaining power operates in the way I have described here, but could provide a way of estimating, rather than fixing, α using only supply-side data concerning the impact of *variations* in bargaining power alongside that assumption. As noted, the demand side of the labor market is also a key contributor to these interrelationships, and should be analyzed more directly. All this remains for future research.

Appendix for Chapter 1

Figure 1: Child Care Subsidy Levels by State



Each line represents the child care subsidy trajectory of a specific state or state group. Lines on this graph represent the eleven states in the top quartile of the standard deviation of their subsidy maximum over time.

Table 1: Summary Statistics by Selected Groups

	All	Female	White	Black	HS or Less	Assoc or Voc	Bachelor's or More
Churn Rate	0.94	1.01	0.85	1.21	1.06	0.96	0.74
–Firing Churn	0.04	0.04	0.04	0.06	0.05	0.05	0.02
–Layoff Churn	0.19	0.18	0.17	0.25	0.22	0.19	0.14
–Match Quit Churn	0.09	0.10	0.10	0.11	0.10	0.11	0.09
–Life Quit Churn	0.20	0.26	0.19	0.23	0.21	0.21	0.15
–Unknown Churn	0.44	0.46	0.39	0.59	0.50	0.43	0.36
Hispanic	0.13	0.13	0.00	0.00	0.22	0.09	0.05
Black	0.12	0.13	0.00	1.00	0.13	0.12	0.07
Other NWNH	0.06	0.06	0.00	0.00	0.05	0.05	0.09
Limiting disability	0.10	0.11	0.10	0.17	0.15	0.10	0.04
Married	0.63	0.64	0.67	0.41	0.59	0.65	0.70
Less than HS	0.09	0.08	0.05	0.09	0.24	0.00	0.00
HS Grad	0.29	0.27	0.28	0.34	0.76	0.01	0.00
Some college	0.33	0.35	0.34	0.39	0.00	0.97	0.00
College Grad	0.19	0.20	0.22	0.13	0.00	0.02	0.67
Grad School	0.10	0.10	0.11	0.06	0.00	0.00	0.33
Age	41.38	41.45	41.97	41.00	41.31	42.17	41.32
Num. children	1.00	1.08	0.92	1.01	1.04	0.99	0.98
High Serv	0.41	0.44	0.46	0.31	0.16	0.38	0.76
Mid Serv	0.19	0.31	0.18	0.25	0.19	0.23	0.11
Low Serv	0.14	0.16	0.12	0.16	0.21	0.12	0.06
Manual	0.26	0.09	0.24	0.27	0.43	0.27	0.06
Observations	81477	42346	56740	9935	31025	11315	23005

Observations are individual respondents. Age, children, and churn rates are measured at the end of the panel. Occupational category is recorded as the modal in-panel value for each individual.

Table 2: Summary Statistics by Total Number of Separations In-Panel

	All	0	1	2	3	4 or More
Churn Rate	0.94	0.00	3.68	6.04	8.54	11.52
Firing Churn	0.04	0.00	0.15	0.29	0.44	0.76
Layoff Churn	0.19	0.00	0.65	1.38	2.35	3.14
Match Quit Churn	0.09	0.00	0.31	0.71	1.24	1.84
Life Quit Churn	0.20	0.00	0.77	1.29	1.56	2.37
Unknown Churn	0.44	0.00	1.79	2.72	3.65	4.85
Hispanic	0.13	0.13	0.15	0.17	0.18	0.19
Black	0.12	0.11	0.14	0.16	0.15	0.11
Other NWNH	0.06	0.06	0.06	0.07	0.05	0.08
Limiting disability	0.10	0.10	0.13	0.14	0.16	0.16
Married	0.63	0.65	0.60	0.56	0.51	0.42
Less than HS	0.09	0.09	0.10	0.12	0.14	0.11
HS Grad	0.29	0.28	0.30	0.32	0.34	0.29
Some college	0.33	0.33	0.34	0.34	0.37	0.42
College Grad	0.19	0.20	0.18	0.15	0.10	0.15
Grad School	0.10	0.10	0.08	0.06	0.05	0.03
Age	41.38	41.61	40.72	39.81	39.78	39.68
No. children in family	1.00	0.99	1.04	1.11	1.14	0.95
High Serv	0.41	0.43	0.35	0.28	0.20	0.20
Mid Serv	0.19	0.18	0.20	0.21	0.23	0.19
Low Serv	0.14	0.13	0.17	0.18	0.20	0.23
Manual	0.26	0.26	0.28	0.33	0.37	0.38
Observations	81477	64146	13177	3090	823	241

Observations are individual respondents. Columns 2-6 divide the sample by the number of job separation events the individual experiences during the panel. Age, children, and churn rates are measured at the end of the panel. Occupational category is recorded as the modal in-panel value for each individual.

Table 3: Impact of Job Churn on Outcomes

	Log Wage	Lack HI	Poor Hlth	Food Inad	Own Home	Prop Val	Welfare
OLS: Supply-Side Churn							
Churn Rate	-.017***	.009***	.009	.012***	-.012***	-.141***	.009***
Female	-.210***	-.077***	.021	-.019	.081***	1.133***	.095***
Black	-.084***	.041***	.193***	.097***	-.216***	-2.881***	.143***
Hispanic	-.223***	.150***	.140***	.066***	-.109***	-1.325***	.090***
Other NWNH	-.038*	.022***	.120***	-.009	-.078***	-.882***	.026***
Limiting disability	-.136***	.006	1.067***	.222***	-.091***	-1.238***	.086***
HS Grad	-.155***	.022***	.079***	.021*	-.040***	-.563***	.020***
Age	.034***	-.013***	-.014	-.002	.040***	.520***	-.024***
Age squared	-.0003***	.0001***	.0003	-4.19e-06	-.0004***	-.005***	.0003***
Mid Serv	-.323***	.040***	.113***	.065***	-.093***	-1.285***	.030***
Low Serv	-.588***	.164***	.200***	.135***	-.180***	-2.418***	.094***
Manual	-.391***	.103***	.197***	.096***	-.128***	-1.737***	.064***
Const.	2.452***	.368***	2.462***	1.431***	-.411***	-6.271***	.497***
Obs.	449189	464849	12938	12978	29279	29183	464849
OLS: Demand-Side Churn							
Churn Rate	-.019***	.017***	.033***	.043***	-.018***	-.211***	.013***
Obs.	449189	464849	12938	12978	29279	29183	464849
2SLS: All Churn, Policy IV							
Churn Rate	-1.022***	.094***	.	.	.	.	.
Obs.	448057	463699	.	.	.	.	.
First Stg. F-test	21.00	20.66	.	.	.	.	.

OLS and policy IV results for the effects of individual quit history on the following outcomes: wages, lack of health insurance, poor health, food inadequacy, home ownership, property value given ownership, and welfare recipiency. Outcomes in columns 3-6 are taken from topical modules in specific panel waves. State and year dummies included as regressors in OLS models; all controls present in the top panel are also used in estimation in the middle and bottom panels. Policy instruments: child care subsidy maxima, worker's compensation generosity, unemployment insurance maxima, minimum wage levels. *$p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 4: Layoff Rate

	All	HS or Less	Some College	Bach or More	HiServ	MidServ	LoServ	Manual
Female	.030***	.080***	.016	.003	.008	.052*	.048*	.115***
Black	.036**	.057**	.054**	-.013	.019	.031	.074*	.156***
Hispanic	.036*	.024	.080*	-.030	.001	.059	.031	.142***
Other NWNH	.044**	.023	.086**	.018	.034	.061	.055	.124*
Limiting disability	.092***	.054*	.135***	.089**	.140***	.140***	.143***	.097**
Married	-.063***	-.061***	-.062***	-.069***	-.059***	-.072***	-.026	-.111***
HS Grad	-.045*	-.040	.	.	.018	-.122*	.060	-.086*
Some college	-.070**	.	.	.	-.042	-.137*	-.007	-.090*
College Grad	-.065**	.	.	.	-.014	-.179**	-.001	-.176***
Grad School	-.085***	.	.	-.026*	-.064	-.178**	.031	-.121
Age	-.016*	-.010	-.029	-.008	-.010	-.040	-.034*	-.007
Age squared	.0002	.00009	.0003	.00007	.00009	.0004	.0004	.0001
CC Rate	-.008	-.028	.015	-.010	-.012	.049	-.078**	-.023
Workers' Comp	-.013	-.025	.023	-.036	-.016	.047	.045	-.079
UI Max	-.0002	-.00009	-.00008	-.0005*	-.0006**	.0003	-.001*	.0003
State minimum wage	-.001	-.004	-.0004	.003	.003	-.019	-.004	.004
Const.	.848***	.817*	1.175**	.209	.292	1.492**	1.463**	1.249*
Obs.	1534381	513613	540014	480754	713343	329429	237908	418754

OLS coefficients in regressions for individual layoff frequencies. Column 1 are estimates from the full working sample, subsequent columns from noted subsamples. *$p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 5: Churn Rate

	Churn	Firing	Layoff	Match Quit	Life Quit
CC Rate	-.068***	-.001	-.009	-.018**	-.028**
Female	.097***	-.005	-.007	.004	.115***
Age	-.087***	-.004	-.012	-.014***	-.037***
Age squared	.0008***	.00003	.0001	.0001**	.0004***
Const.	3.983***	.211**	.898***	.608***	1.437***
Obs.	1925249	1925249	1925249	1925249	1925249
Children in Household					
All	-.069*	.0001	-.015	-.028**	-.022
Women	-.085	.005	-.021	-.039**	-.035
Men	-.048	-.006	-.008	-.012	-.004
Low Serv	-.323**	-.023	-.093	-.122**	-.051
No Children, HS or Less					
Women	-.249***	-.00007	-.176***	-.005	-.019
High Serv	-.031	-.028	-.156*	.038	.061*
Low Serv	-.302**	.035	-.105*	-.051	-.132**
No Kids, HS, Labor Force					
Women	-.323***	-.009	-.213***	-.009	-.057
Controls	Y	Y	Y	Y	Y

OLS coefficients in regressions for overall churn and different types of churn rates. Coefficients in panels 2-4 represent the effect of the child care subsidy maximum on churn in the subsample described at the top of the panel. *$p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 6: Layoff Hazard Rates, Low-Education Women

	Young NK	Young K	Old NK	Old K
CC Rate	-.320*	.030	-.167	-.0005
Workers' Comp	-.378	.144	-.160	.335**
UI Max	.004	-.0002	.003**	.001
State minimum wage	.309	-.008	-.203	.223
Black	.560	-.141	.159	.602**
Hispanic	.661	.176	.064	.139
Other NWNH	.	-.003	.702*	.115
Limiting disability	.296	.219	-.079	.775**
Married	.469	-.260	-.033	.278
HS Grad	-.434	-.306*	-.467**	-.537**
Age	-.418	-.034	.058	-.172
Age squared	.006	-.0001	-.0006	.002
Const.	-1.937	-3.603	-6.419	-3.730
Obs.	16976	69926	73168	62140

Hazard rate coefficients on child care subsidy maxima from complementary log-log estimation of event risk. *$p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 7: Churn Rate — CC Receipt Interaction, ≤HS Only

	Churn	Firing	Layoff	Match Quit	Life Quit	Unknown
CC Rate	-.084*	.022*	-.030	-.019	-.002	-.054**
Ever rec CC subsidy	.744***	.144**	-.016	.282**	.290***	.151
Rec CC*CC Rate	-.042	-.007	.103	-.044	-.156**	-.012
Female	.316***	-.002	.080***	.016	.145***	.077***
Black	.156***	-.003	.057**	-.020	-.015	.114***
Hispanic	.058	-.035**	.023	-.056**	.029	.073**
Other NWNH	.170*	-.007	.023	-.033	.035	.123**
Limiting disability	.799***	.087***	.054*	.034	.344***	.271***
Married	-.210***	-.051***	-.061***	-.038***	-.004	-.067***
HS Grad	-.258***	-.028**	-.040	-.031	-.047**	-.126***
Age	-.065**	-.007	-.010	-.010	-.030***	-.006
Age squared	.0005*	.00006	.00009	.00005	.0003**	-.00003
Workers' Comp	.111	.005	-.026	-.038	.098***	.078
UI Max	-.0004	.00003	-.00009	.00002	-.00003	-.0004
Const.	2.383***	.260*	.802*	.273	.677**	.377
Obs.	513704	513704	513704	513704	513704	513704
Women						
CC Rate	-.181**	.009	-.068**	-.038*	-.029	-.068*
Ever rec CC subsidy	.675***	.162**	-.023	.217*	.278**	.136
Rec CC*CC Rate	-.028	-.007	.107	-.056	-.155**	.003
Obs.	246620	246620	246620	246620	246620	246620
Women with Children						
CC Rate	-.115	.017	.011	-.062*	-.027	-.066
Ever rec CC subsidy	.579***	.165**	-.015	.204*	.212*	.114
Rec CC*CC Rate	-.008	-.011	.104	-.072	-.123*	.006
Obs.	147710	147710	147710	147710	147710	147710

OLS coefficients in regressions for overall churn and different types of churn rates. Coefficients in panels 2-3 represent the effect of the child care subsidy maximum on churn in the subsample described at the top of the panel. *$p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 8: FIXED MODEL PARAMETERS

ϕ_1	0.0019	ϕ_2	0.0083
p_1	0.768	p_2	0.696
α	0.3	p_3	0.585
ρ	0.008	p_4	0.400
w^*	2.25		

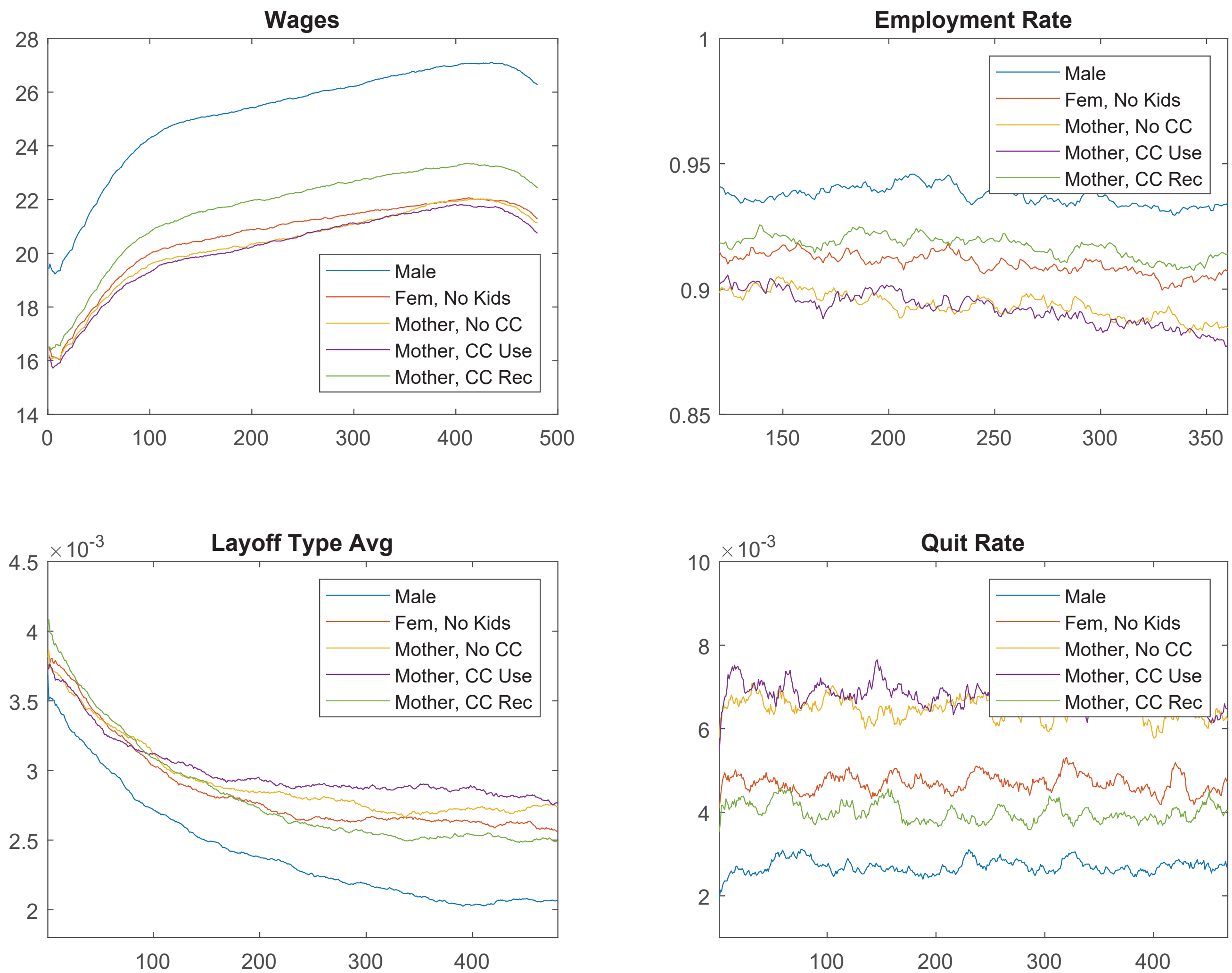
Parameter values fixed prior to structural estimation. The right-hand panel parameters — the high layoff rate ϕ_2 and the draw probabilities p_1, p_2, and p_3 — are estimated in a first-step maximum likelihood procedure based on the selected values of ϕ_1 and p_4 and initial guesses of all other parameters as described in the text.

Table 9: Model Parameters

λ^{θ}	0.131	β_1	-2.829
	(.001)		(.020)
μ_1	3.840	$\beta_2^{Fem,NoKid}$	0.176
	(.010)		(.020)
μ_2	3.595	β_2^{Mother}	0.246
	(.012)		(.021)
μ_3	3.401	β_3^{Black}	-0.018
	(.015)		(.018)
μ_4	3.655	$\beta_3^{Hispanic}$	-0.038
	(.014)		(.018)
μ_{fem}	0.002	β_4^{SC}	-0.042
	(.007)		(.013)
μ_{min}	-0.176	β_5	-0.257
	(.006)		(.013)
μ_{sc}	0.144	β_6	0.017
	(.005)		(.027)
μ_{hi}	-0.065	β_7	0.040
	(.015)		(.008)
σ_1	0.587	β_8	0.149
	(.007)		(.109)
σ_2	0.575	β_9	-0.002
	(.008)		(.0008)
σ_3	0.625	$\beta_{10,2}$	0.055
	(.008)		(.018)
σ_4	0.656	$\beta_{10,3}$	0.242
	(.008)		(.018)
σ_{fem}	0.855	$\beta_{10,4}$	0.057
	(.008)		(.019)
σ_{min}	1.024		
	(.009)		
σ_{sc}	1.043		
	(.009)		
σ_{hi}	0.676		
	(.011)		
c^q	2498.49		
	(124.31)		

Parameter estimates from maximum likelihood estimation of search model; standard errors in parentheses beneath each estimate. The β in the right-hand panel are estimated in a separate probit as described in the text.

Figure 2: Outcome Paths by Group in Base Simulation

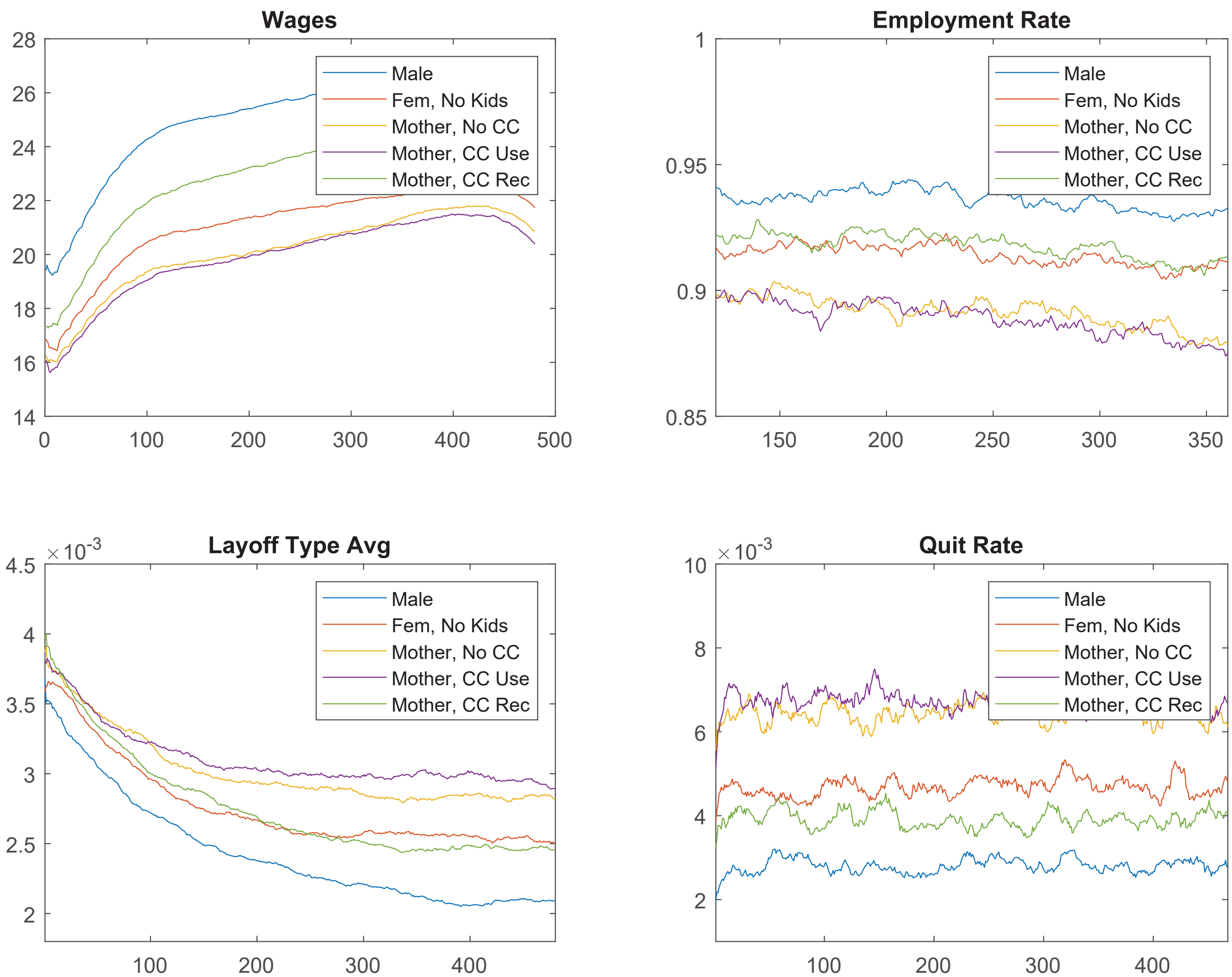


Mean values of wages, employment, and ϕ values as well as quit frequencies by subgroup in simulation with statistical discrimination and variable child care subsidy maxima based on true distribution. All simulants begin at time 0 without a job and with permanent characteristics with regard to parent status, child care and subsidy user status, race, and education (high school or less).

Figure 3: Outcome Paths by Group in SIPP Data

Mean values of wages and employment as well as quit and layoff frequencies by subgroup in SIPP data at ages corresponding to simulation ranges in Figure 2.

Figure 4: Outcome Paths by Group in Simulation with Full Information



Mean values of wages, employment, and ϕ values as well as quit frequencies by subgroup in simulation with firm access to full applicant information (and thus no statistical discrimination) and variable child care subsidy maxima based on true distribution. All simulants begin at time 0 without a job and with permanent characteristics with regard to parent status, child care and subsidy user status, race, and education (high school or less).

Table 10: Simulated Mean Outcomes By Scenario

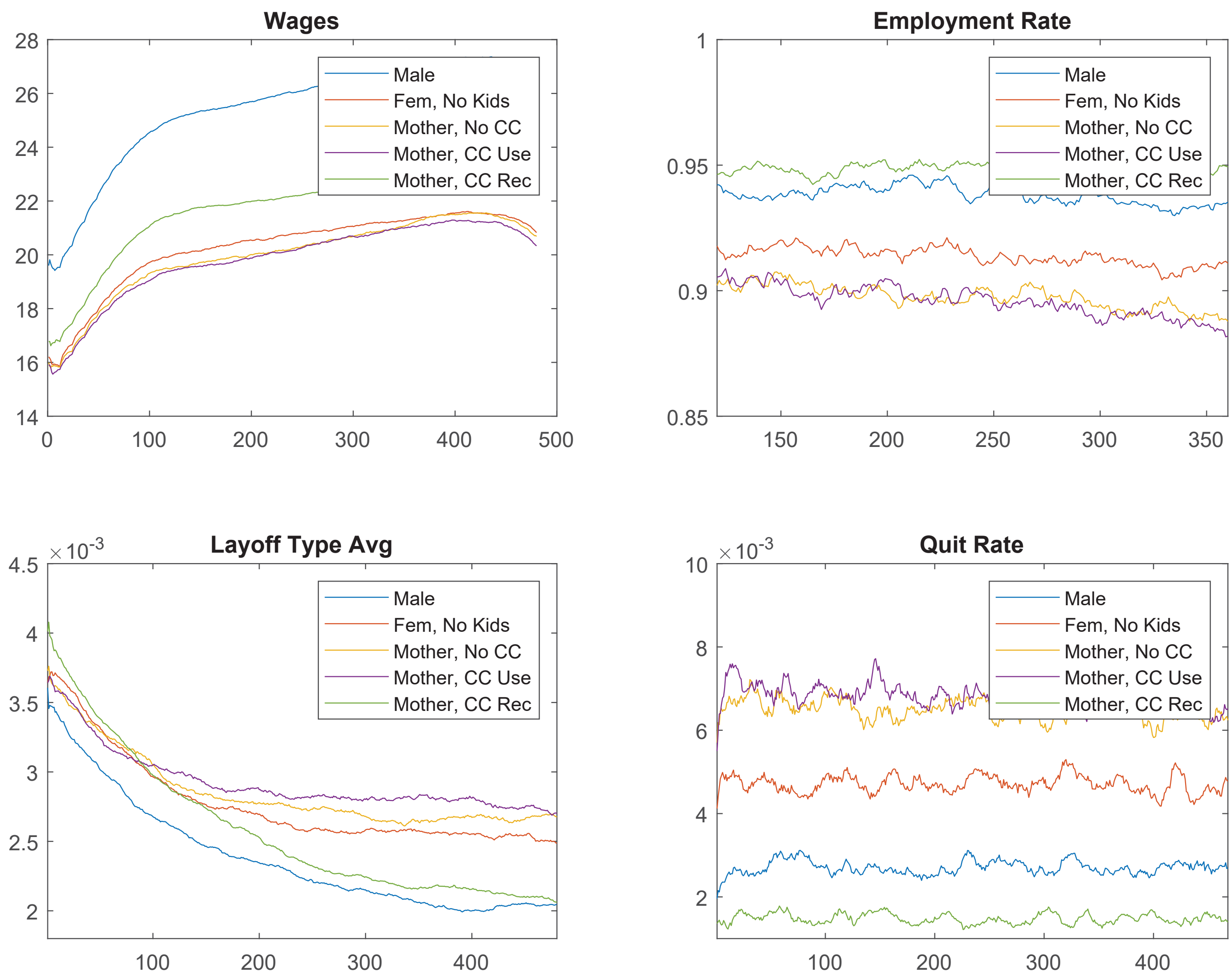
	Base Sim	Full Info	Max CC Sub	No CC Sub
Wages ($)				
Men	25.77			
Childless Women	21.08	21.58	21.02	21.13
Mothers	20.92	20.95	20.91	20.81
Quit Rates (%)				
Men	0.270			
Childless Women	0.475	0.474	0.476	0.474
Mothers	0.604	0.603	0.562	0.678
Employment Rates (%)				
Men	93.7			
Childless Women	91.0	91.4	91.5	90.8
Mothers	89.8	89.6	90.7	88.8
Layoff Rates (%)				
Men	0.233			
Childless Women	0.266	0.259	0.257	0.271
Mothers	0.278	0.287	0.266	0.290

Mean outcome values for middle 20 years (out of 40) in simulation by subgroup and counterfactual scenario.

Figure 5: Outcome Paths by Group in Simulation with Zero Subsidy Allowances

Mean values of wages, employment, and ϕ values as well as quit frequencies by subgroup in simulation with statistical discrimination and child care subsidy maxima set to zero for all individuals. All simulants begin at time 0 without a job and with permanent characteristics with regard to parent status, child care and subsidy user status, race, and education (high school or less).

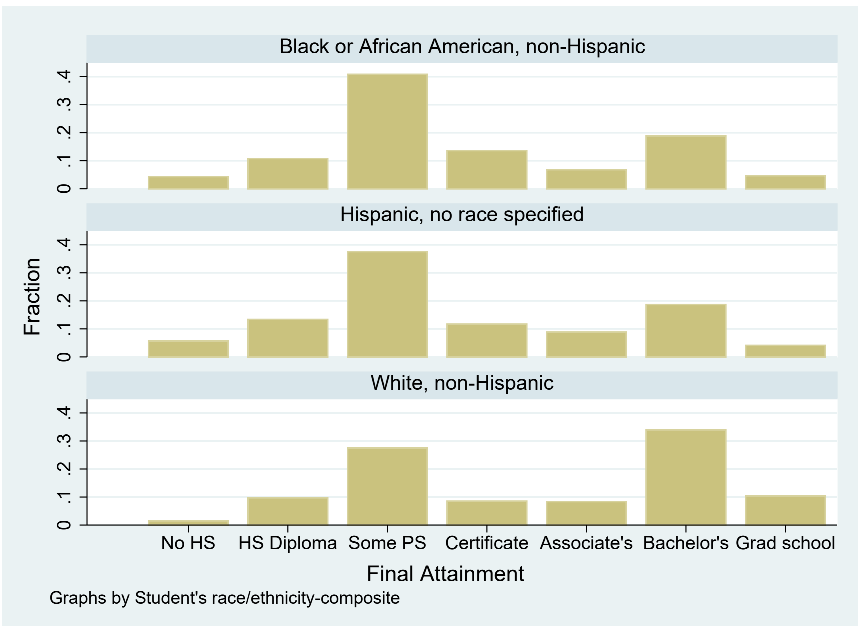
Figure 6: Outcome Paths by Group in Simulation with Maximal Subsidy Allowances



Mean values of wages, employment, and ϕ values as well as quit frequencies by subgroup in simulation with statistical discrimination and child care subsidy maxima set to \$275 per month, the largest value for any state in the 2001-2007 period, for all individuals. All simulants begin at time 0 without a job and with permanent characteristics with regard to parent status, child care and subsidy user status, race, and education (high school or less).

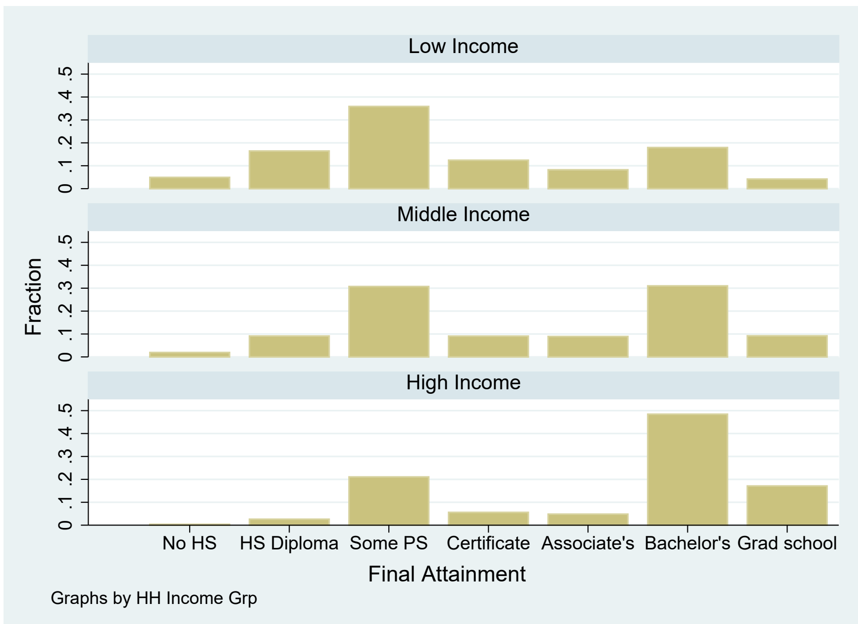
Appendix for Chapter 2

Figure 7: Final Attainment by Race



Final attainment of ELS respondents, sorted by race and ethnicity. “Some PS” indicates that the respondent attended some postsecondary educational institution, but received no credential of any kind.

Figure 8: Final Attainment by HH Income



Final attainment of ELS respondents, sorted by household income during youth. "Some PS" indicates that the respondent attended some postsecondary educational institution, but received no credential of any kind. "Low income" includes households earning less than $35k per year, "high income" those earning more than $100k per year, and "middle income" those between the two thresholds.

Table 11: Data Features

	NLSY97	ELS2002	HSLS2009
Timeframe	1997-2013	2002-2012	2009-2016
Start	Ages 12-18	10th Grade	9th Grade
Test scores	Standardized	Survey-admin.	Survey-admin. math
HS GPA	Yearly	Total	Yearly
Certificate?	No	Yes	Yes
Educ. expectation	Pct. chance bach.	Final attainment	Final attainment
Shock expectation	Pct. chance	None	None
Exp. elicitation	1997	All four waves	All three waves
Reason incomplete	No	Yes	Yes
Final attainment?	Yes	Yes	No
Observations	8,984	16,197	23,503

Essential features of the three data sets used. "Certificate?" denotes whether the data include an indicator for earning a postsecondary certificate, short of an associate's degree. "Shock expectation" describes how (in the NLSY) expectations for future adverse shocks, such as victimization and pregnancy, are recorded. "Reason incomplete" indicates whether the data include responses regarding the reason(s) the individual dropped out of any educational institution.

Table 12: NLSY SUMMARY STATS BY ATTAINMENT

	All	No Deg	HS	Some Coll	College
Black	0.26	0.29	0.29	0.29	0.17
Hispanic	0.21	0.31	0.23	0.22	0.14
Low income	0.40	0.61	0.50	0.39	0.20
Mid income	0.39	0.21	0.34	0.40	0.50
Mother: no degree	0.23	0.46	0.31	0.19	0.08
Mother: HS diploma	0.36	0.34	0.42	0.39	0.25
Mother: some coll	0.24	0.15	0.20	0.26	0.29
Mother: Bachelor's	0.18	0.05	0.07	0.16	0.38
GPA 1-2	0.08	0.22	0.14	0.07	0.01
GPA 2-3	0.50	0.60	0.64	0.56	0.27
GPA 3 and up	0.41	0.12	0.20	0.36	0.72
Math score	-0.12	-0.81	-0.54	-0.25	0.26
Verbal score	-0.09	-0.44	-0.60	-0.31	0.19
Observations	8984	969	2897	2731	2355

NLSY means for group indicator variables and standardized test scores. Test scores have themselves been statistically standardized. The "Some Coll" column includes all individuals who attended some kind of postsecondary institution but never earned a bachelor's degree (but may have a lesser credential like an associate's degree).

Table 13: ELS Summary Stats By Attainment

	All	No Deg	HS	Some Coll	College
Black	0.12	0.19	0.12	0.15	0.07
Hispanic	0.14	0.28	0.17	0.16	0.08
Low income	0.28	0.49	0.42	0.31	0.15
Mid income	0.53	0.38	0.46	0.54	0.56
Mother: no degree	0.13	0.38	0.23	0.13	0.05
Mother: HS diploma	0.27	0.33	0.40	0.29	0.18
Mother: some coll	0.33	0.20	0.28	0.37	0.31
Mother: Bachelor's	0.27	0.09	0.09	0.21	0.45
GPA 1-2	0.17	0.59	0.36	0.20	0.02
GPA 2-3	0.41	0.22	0.47	0.51	0.25
GPA 3-4	0.40	0.02	0.13	0.28	0.73
Math score	50.71	40.73	44.36	49.04	56.87
Reading score	50.53	40.85	44.66	49.17	56.39
Observations	16197	356	1388	6406	5100

Table 14: Expectations By Attainment

	All	No Deg	HS	Some Coll	College
ELS					
No Diploma	0.01	0.06	0.03	0.01	0.00
HS Only	0.07	0.32	0.24	0.06	0.01
Some College	0.10	0.22	0.22	0.13	0.03
Bachelor's	0.39	0.25	0.35	0.42	0.36
Graduate Deg	0.42	0.15	0.15	0.38	0.60
Observations	16019	352	1368	6346	5067
NLSY					
Coll exp 0-25	0.13	0.31	0.23	0.08	0.01
Coll exp 25-50	0.18	0.30	0.25	0.17	0.05
Coll exp 50-75	0.13	0.09	0.13	0.15	0.11
Coll exp 75-100	0.56	0.30	0.39	0.60	0.83
Observations	3546	370	1164	1069	930
Exp: crime victim	14.70	16.64	15.91	15.53	11.43
Exp: arrest	10.22	15.08	11.80	10.51	6.06
Exp: death	18.64	21.06	20.20	19.04	15.30
Exp: pregnancy	7.90	15.24	9.50	6.96	3.97
Observations	3531	367	1156	1068	926

Average expectations responses from the ELS and NLSY. ELS educational attainment expectations are by final attainment expected; NLSY expectations are stated as a percent chance of completing a bachelor's degree, and are sorted into quartiles. NLSY expectations over other adverse events are stated as a percent chance for the event to occur in the next year. The "Some Coll" column includes all individuals who attended some kind of postsecondary institution but never earned a bachelor's degree (but may have a lesser credential like an associate's degree).

Table 15: LPM for College Attainment with Demographics, Shocks, and Expectations: NLSY

	(1) College grad	(2) College grad	(3) College grad	(4) College grad	(5) College grad
Coll exp 25-50	0.05**	0.04	0.04	0.04	0.10
Coll exp 50-75	0.24***	0.16***	0.14***	0.14***	0.20***
Coll exp 75-100	0.42***	0.28***	0.25***	0.25***	0.26***
Black		-0.06**	-0.02	-0.02	0.14***
Hispanic		-0.11***	-0.11***	-0.11***	-0.11**
Asian or PI		0.15**	0.15**	0.14*	0.05
Native American		-0.04	0.06	0.05	0.13
Multiple races		-0.12	-0.11	-0.11	-0.13
Male		-0.06***	-0.06***	-0.06***	-0.07**
Low income		-0.16***	-0.11***	-0.11***	-0.02
Mid income		-0.06*	-0.04	-0.04	0.02
Mother has no degree		-0.31***	-0.30***	-0.30***	-0.12**
Mother has HS diploma		-0.28***	-0.28***	-0.28***	-0.19***
Mother has some college		-0.18***	-0.18***	-0.18***	-0.11***
Break-in by 18			-0.06**	-0.06**	-0.06
Bullied by 18			-0.04	-0.04	-0.02
Seen shooting by 18			-0.07**	-0.06**	-0.06
Feels unsafe			-0.08***	-0.08***	-0.06***
Victim of crime			-0.01	-0.01	-0.04
Ever homeless, 1997-2002			-0.14***	-0.15***	-0.42**
No mother or female guardian in HH			0.00	0.00	0.00
No father or male guardian in HH			-0.03	-0.03	-0.03
Changed schools			-0.09***	-0.08***	-0.05
Parent died			-0.07	-0.07	-0.14
Other family died			-0.03	-0.02	-0.04
Parent hospitalized			-0.03	-0.03	-0.06
Parent jailed			-0.09	-0.08	-0.08
Parents divorced			-0.04	-0.04	-0.09
Parent unemp			-0.00	-0.00	0.05
Sibling count			-0.01	-0.01	-0.02
Expect: victim of crime				0.00	-0.00
Expect: arrest				-0.00	-0.00
Expect: death				-0.00*	-0.00
Expect: pregnancy				0.00	0.00
Expect: get drunk				-0.00*	0.00
GPA 3 and up					0.67***
GPA 2-3					0.51***
GPA 1-2					0.28*
Verbal score					0.05**
Math score					0.07***
Constant	0.04***	0.49***	0.69***	0.72***	0.03
Adjusted R^2	0.12	0.23	0.26	0.26	0.26
Observations	1954	1954	1954	1954	1028

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 16: LPM for College Attainment with Demographics, Shocks, and Expectations: ELS

	(1)	(2)	(3)	(4)
Expects > 4 year degree (student)	(Omitted)			
Expects no degree (student)	-0.38***	-0.24***	-0.09***	-0.08***
Expect HS diploma (student)	-0.29***	-0.22***	-0.09***	-0.08***
Expects some college (student)	-0.29***	-0.22***	-0.13***	-0.12***
Expects 4 year degree (student)	-0.11***	-0.09***	-0.04***	-0.04***
Expects > 4 year degree (parent)	(Omitted)			
Expects no degree (parent)	-0.50***	-0.39***	-0.14***	-0.11**
Expects HS diploma (parent)	-0.41***	-0.33***	-0.14***	-0.14***
Expects some college (parent)	-0.38***	-0.34***	-0.18***	-0.18***
Expects 4 year degree (parent)	-0.11***	-0.10***	-0.04***	-0.03***
White	(Omitted)			
Black		-0.14***	0.01	0.01
Latino/a		-0.17***	-0.06***	-0.06***
Asian		0.05**	0.04*	0.04*
Native		-0.21***	-0.10**	-0.09*
Multiple races		-0.14***	-0.08***	-0.07***
High income	(Omitted)			
Low income		-0.14***	-0.11***	-0.12***
Middle income		-0.07***	-0.07***	-0.07***
Controls for mother's education	No	Yes	Yes	Yes
Controls for academic ability	No	No	Yes	Yes
Controls for all shocks	No	No	No	Yes
Adj. R^2	0.17	0.23	0.33	0.33
N	6,553	6,553	6,553	6,553

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 17: Attainment by Type of First PS School: NLSY

	(1) Pub2 mean/sd	(2) NP2 mean/sd	(3) FP2 mean/sd	(4) Pub4 mean/sd	(5) NP4 mean/sd	(6) FP4 mean/sd
No postsec	0.00	0.00	0.00	0.00	0.00	0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Some college	0.74	0.74	0.89	0.33	0.26	0.71
	(0.44)	(0.44)	(0.32)	(0.47)	(0.44)	(0.45)
No credential	0.53	0.46	0.50	0.27	0.21	0.56
	(0.50)	(0.51)	(0.50)	(0.45)	(0.41)	(0.50)
Associates	0.22	0.28	0.38	0.06	0.05	0.15
	(0.41)	(0.46)	(0.49)	(0.23)	(0.22)	(0.36)
College grad	0.26	0.26	0.11	0.67	0.74	0.29
	(0.44)	(0.44)	(0.32)	(0.47)	(0.44)	(0.45)
Observations	1992	39	244	1813	713	91

NP = Nonprofit; FP = For-profit; Pub = Public; 2 = two yr. or less; 4 = four yr.

Table 18: Attainment by Type of First PS School: ELS

	Public 2	NP 2	FP 2	Public 4	NP 4	FP 4
Some college	0.78	0.71	0.96	0.35	0.27	0.73
No PS credential	0.47	0.42	0.38	0.24	0.20	0.47
PS certificate	0.15	0.19	0.41	0.05	0.04	0.12
PS associates	0.16	0.10	0.18	0.05	0.04	0.14
College or more	0.22	0.29	0.04	0.65	0.73	0.27
White	0.52	0.54	0.43	0.59	0.65	0.41
Black	0.13	0.15	0.19	0.11	0.10	0.19
Hispanic	0.16	0.13	0.20	0.09	0.07	0.20
Low income	0.32	0.23	0.37	0.19	0.15	0.34
Middle income	0.54	0.60	0.50	0.56	0.53	0.50
High income	0.09	0.14	0.05	0.21	0.29	0.09
Observations	3,426	59	357	3,927	2,013	182

NP = Nonprofit; FP = For-profit; 2 = two yr. or less; 4 = four yr.

Table 19: MNL for Attainment with First PS School Type: NLSY

	(1) Att Coll	(2) Associates	(3) Bachelors	(4) Adv Deg
Black	0.12***	-0.03**	-0.09***	-0.01
Hispanic	0.07***	-0.04**	-0.01	-0.02
Asian or PI	-0.03	-0.05	0.02	0.06**
Native American	0.01	-0.02	0.10	-0.09
Multiple races	-0.00	-0.02	0.03	-0.00
Male	0.09***	-0.01	-0.03**	-0.05***
Low income	0.04**	0.04***	-0.05**	-0.03*
Mid income	-0.01	0.03**	-0.02	0.00
Mother has no degree	0.14***	0.03*	-0.07***	-0.10***
Mother has HS diploma	0.12***	0.03**	-0.05***	-0.10***
Mother has some college	0.05***	0.01	-0.01	-0.05***
PrivNP2 school	-0.07	0.04	0.09	-0.06
PrivFP2 school	0.03	0.10***	-0.06	-0.07
Pub4 school	-0.16***	-0.16***	0.19***	0.12***
PrivNP4 school	-0.23***	-0.14***	0.22***	0.14***
PrivFP4 school	0.02	-0.04	0.11*	-0.09
Adjusted R^2				
Observations	4478	4478	4478	4478

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 20: MNL for Attainment with First PS School Type: ELS

	(1) No credential	(2) Certificate	(3) Associates	(4) College+
White	(Omitted)			
Black	0.03**	-0.00	-0.03***	-0.00
Latino/a	0.03**	-0.01	-0.00	-0.01
Asian	-0.00	-0.02*	-0.04***	0.06***
Native	0.07	0.01	-0.01	-0.07
Multiple races	0.04*	-0.00	-0.00	-0.04*
Male	0.06***	-0.03***	-0.01	-0.02**
High income	(Omitted)			
Low income	0.05***	0.02	0.02*	-0.08***
Middle income	0.01	0.00	0.03***	-0.04***
Public, 2 year or less	(Omitted)			
Nonprofit, 2 year or less	-0.05	0.02	-0.03	0.06
For-profit, 2 year or less	0.04	0.12***	0.05***	-0.21***
Public, 4 year	-0.08***	-0.05***	-0.06***	0.20***
Nonprofit, 4 year	-0.10***	-0.06***	-0.08***	0.24***
For-profit, 4 year	-0.06*	-0.03	0.01	0.08***
Controls for mother's education	Yes	Yes	Yes	Yes
Controls for academic ability	Yes	Yes	Yes	Yes
N	10,078	10,078	10,078	10,078

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 21: MNL FOR FIRST PS SCHOOL TYPE: NLSY

	(1) Pub2	(2) FP2	(3) Pub4	(4) NP4	(5) FP4
Coll exp 25-50	-0.01	0.03	0.10	-0.08	-0.03**
Coll exp 50-75	-0.21***	0.02	0.21**	0.01	-0.03**
Coll exp 75-100	-0.28***	0.00	0.26***	0.04	-0.03***
Black	-0.05	0.01	0.05*	-0.01	-0.00
Hispanic	0.07**	0.02	-0.03	-0.06*	0.00
Asian or PI	-0.11	0.04	0.04	0.00	0.02
Native American	1.50	0.22	1.70	-3.50	0.09
Multiple races	0.69	-0.63	0.12	0.01	-0.19
Male	-0.01	-0.02	0.03	0.00	-0.00
Low income	0.07*	0.03	-0.05	-0.07***	0.03
Mid income	0.03	0.02	-0.02	-0.06***	0.03
Mother no degree	0.14***	0.05*	-0.10**	-0.08**	0.00
Mother has HS diploma	0.09***	0.05**	-0.08**	-0.06***	0.01
Mother has some college	0.07**	0.02	-0.05	-0.04*	-0.00
GPA 3 and up	-0.34	-0.09	0.26	-0.03	0.20
GPA 2-3	-0.16	-0.04	0.08	-0.10	0.21
GPA 1-2	0.09	-0.02	-0.23	-0.04	0.20
Adjusted R^2					
Observations	1645	1645	1645	1645	1645

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 22: HSLS Summary Statistics

Pub2 school	0.27
PrivNP2 school	0.01
PrivFP2 school	0.03
Pub4 school	0.41
PrivNP4 school	0.18
PrivFP4 school	0.01
Feels unsafe	1.76
	(0.66)
Shocks, 09-11	1.00
	(1.16)
Shocks, 11-16	0.84
	(0.95)
Exp bach plus, 2011	0.62
	(0.49)
Exp. earnings, no diploma	15.39
	(8.14)
Exp. earnings, HS diploma	20.16
	(13.60)
Exp. earnings, certificate	27.12
	(18.37)
Exp. earnings, Associate's	33.23
	(22.08)
Exp. earnings, Bachelor's	49.93
	(32.82)
Thinks def capable of BA	0.49
Fin aid: will qual	0.43
Fin aid: won't qual	0.26
Fin aid: unsure	0.31
Plans bach enroll, 2009	0.53
Observations	23495

HSLS means for postsecondary school type indicator variables, adverse shocks, and expectations. NP = Nonprofit; FP = For-profit; Pub = Public; Priv = Private; 2 = two yr. or less; 4 = four yr. "Shocks" variables are sums of various types of adverse shocks over the relevant time period as described in the text. Expected earnings are in thousands of dollars per year. Standard deviations included below means in parentheses where relevant.

Table 23: MNL for First PS Program Type Given Plan to Enroll in Four-Year: HSLS

	(1) Pub2	(2) FP2	(3) Pub4	(4) NP4	(5) FP4
Exp bach plus, 2011	-0.09***	-0.01**	0.06*	0.05*	0.01
Break: Academic	0.68	-0.19	2.07	-1.86	0.04
Break: Family	0.08**	0.02***	0.00	-0.12	-0.00
Break: Financial	0.10**	0.01	-0.13	-0.03	0.02***
Break: Work	0.03	0.01	0.04	-0.13	0.01
Break: Unknown	0.07	0.00	-0.12	0.07	-0.10
Thinks def capable of BA	-0.02	-0.00	0.02	0.01	-0.00
Fin aid: will qual	0.00	0.00	0.00	0.00	0.00
Fin aid: won't qual	-0.01	-0.00	0.05**	-0.04**	0.00
Fin aid: unsure	-0.02	-0.00	0.01	-0.01	0.00
Black	-0.09***	-0.00	0.04	0.07***	0.01*
Hispanic	0.00	0.00	-0.03	0.02	0.00
Asian, HI, PI	-0.10***	0.01	0.11***	-0.03	0.00
Native American	-0.00	-0.14	0.15	0.07	-0.09
Multiple races	0.01	0.01	-0.02	-0.02	0.01**
Male	0.01	-0.02***	0.05***	-0.02*	-0.00
Low income	0.09***	0.01	-0.05*	-0.05**	0.00
Mid income	0.07***	0.02**	-0.07***	-0.03*	0.00
Mother no degree	0.12***	0.01	-0.00	-0.11**	-0.00
Mother has HS diploma	0.05***	0.01*	-0.03	-0.03**	-0.00
Mother has Associate's	0.07***	-0.00	-0.04*	-0.03*	-0.01
GPA: Academic	-0.09***	-0.01***	0.08***	0.06***	-0.01*
GPA: CTE	-0.02*	-0.00	0.04**	-0.01	-0.00
Math score	-0.05***	-0.01**	0.04***	0.03***	0.00
Adjusted R^2					
Observations	3768	3768	3768	3768	3768

"Break" variables indicate that the respondent took a break from school for the stated reason. "Fin aid" variables regard respondents' expectations for educational financial aid qualification. "CTE" indicates Career and Technical Education.

Table 24: MNL FOR FIRST PS PROGRAM TYPE GIVEN PLAN TO ENROLL IN FOUR-YEAR: HSLS

	(1) Pub2	(2) FP2	(3) Pub4	(4) NP4	(5) FP4
Exp bach plus, 2011	-0.17	-0.01	0.02	0.05	0.14
Feels unsafe	0.01	0.00	-0.00	-0.02	0.00
Shocks, 09-11	0.02**	0.00	-0.03**	0.02	-0.00
Thinks def capable of BA	-0.00	-0.00	0.01	-0.00	-0.01
Black	-0.09***	-0.00	0.04	0.09***	0.01
Hispanic	-0.01	0.01	-0.02	0.03	-0.00
Asian, HI, PI	-0.09**	0.02	0.08*	0.02	-0.00
Native American	0.04	-0.20	-0.01	0.23	-0.13
Multiple races	-0.00	0.02*	-0.06	0.03	0.02**
Male	0.01	-0.02**	0.07***	-0.04*	-0.00
Low income	-0.01	0.21	-0.09	-0.10	0.00
Mid income	-0.02	0.22	-0.14	-0.05	0.00
Mother no degree	0.16***	0.00	-0.09	-0.07	0.00
Mother has HS diploma	0.08***	0.00	-0.06**	-0.02	-0.00
Mother has Associate's	0.10***	-0.01	-0.06*	-0.03	-0.01
GPA: Academic	-0.08***	-0.00	0.06**	0.07***	-0.01
GPA: CTE	-0.03*	-0.01**	0.07**	-0.01	-0.00
Math score	-0.05***	-0.01***	0.05***	0.03**	0.00
Adjusted R^2					
Observations	1564	1564	1564	1564	1564

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 25: MNL for Attainment: NLSY

	(1) Att Coll	(2) Associates	(3) Bach or More
Coll exp 25-50	-0.05	0.02	0.04
Coll exp 50-75	-0.09	-0.03	0.12*
Coll exp 75-100	-0.16***	-0.04	0.20***
Black	0.05*	-0.06**	0.01
Hispanic	0.10***	-0.01	-0.08**
Asian or PI	-0.05	-0.07	0.12
Native American	0.02	0.00	-0.02
Multiple races	0.09	-0.01	-0.08
Male	0.06**	-0.03	-0.03
Low income	0.04	0.07**	-0.11***
Mid income	-0.02	0.06**	-0.04
Mother no degree	0.15***	0.07*	-0.21***
Mother has HS diploma	0.14***	0.06**	-0.20***
Mother has some college	0.07*	0.05*	-0.12***
GPA 3 and up	-2.24	-0.90	3.14
GPA 2-3	-2.10	-0.84	2.94
GPA 1-2	-1.81	-0.81	2.61
Adjusted R^2			
Observations	1467	1467	1467

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 26: MNL for Attainment with First PS School Type: NLSY

	(1) Att Coll	(2) Associates	(3) Bach or More
Coll exp 25-50	-0.04	0.02	0.02
Coll exp 50-75	-0.04	-0.02	0.05
Coll exp 75-100	-0.09	-0.01	0.10
Black	0.06**	-0.06**	-0.00
Hispanic	0.09**	-0.03	-0.06
Asian or PI	-0.04	-0.06	0.10
Native American	-0.07	0.00	0.07
Multiple races	0.07	-0.02	-0.05
Male	0.06***	-0.03	-0.04
Low income	0.01	0.06*	-0.06*
Mid income	-0.04	0.05*	-0.01
Mother no degree	0.10**	0.03	-0.13***
Mother has HS diploma	0.10***	0.03	-0.13***
Mother has some college	0.05	0.03	-0.08**
GPA 3 and up	-2.09	-0.71	2.80
GPA 2-3	-1.99	-0.70	2.69
GPA 1-2	-1.76	-0.70	2.45
PrivNP2 school	-0.06	0.07	-0.00
PrivFP2 school	0.03	0.04	-0.07
Pub4 school	-0.10***	-0.17***	0.27***
PrivNP4 school	-0.18***	-0.14***	0.32***
PrivFP4 school	0.95	-1.59	0.65
Adjusted R^2			
Observations	1431	1431	1431

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 27: NLSY Adverse Shock Summary Stats By Attainment

	All	No Deg	HS	Some Coll	College
Absent mother	0.03	0.05	0.04	0.03	0.02
Absent father	0.28	0.37	0.33	0.28	0.19
Changed schools	0.11	0.17	0.14	0.11	0.05
Break-in by 18	0.10	0.12	0.11	0.11	0.07
Bullied by 18	0.10	0.11	0.11	0.10	0.09
Seen shooting by 18	0.12	0.21	0.16	0.13	0.05
Parent died	0.03	0.04	0.04	0.04	0.02
Other family died	0.51	0.52	0.54	0.50	0.48
Parent hospitalized	0.09	0.07	0.09	0.09	0.09
Parent jailed	0.02	0.04	0.03	0.02	0.01
Parents divorced	0.08	0.08	0.08	0.08	0.07
Parent unemp	0.08	0.08	0.08	0.09	0.08
Victim of crime	0.07	0.07	0.08	0.07	0.04
Ever homeless, 97-02	0.02	0.03	0.03	0.01	0.00
Sibling count	1.45	1.71	1.56	1.43	1.24
Observations	8984	969	2897	2731	2355

Table 28: Ordered Probit for Expectations: ELS

Black	-0.15	0.10	0.17	0.32***
Hispanic	-0.25**	-0.08	-0.01	0.05
Asian or PI	0.13	0.15	0.04	-0.11
Native American	-0.20	0.15	0.27	0.53
Multiple races	-0.13	0.12	0.17	0.34
Male	-0.20**	-0.21***	-0.24***	-0.25***
No mother or female guardian in HH		0.00	0.00	0.00
No father or male guardian in HH		-0.04	0.06	0.12
Changed schools		-0.52***	-0.50***	-0.47**
Parent died		-0.18	-0.07	-0.05
Other family died		-0.03	-0.02	-0.05
Parent hospitalized		0.23	0.24	0.22
Parent incarcerated		0.08	0.09	0.17
Parents divorced		-0.33**	-0.30*	-0.31**
Parent unemp		-0.09	-0.05	-0.06
stuhhsibcnt		-0.09**	-0.07**	-0.07*
Break-in by 18		0.56***	0.52***	0.56***
Bullied by 18		0.00	0.01	-0.00
Seen shooting by 18		-0.26**	-0.24*	-0.17
Feels unsafe		-0.43***	-0.42***	-0.39***
Victim of crime		-0.12	-0.09	-0.12
Low income			-0.43***	-0.34**
Mid income			-0.21*	-0.15
Mother has no degree			-0.10	-0.05
Mother has HS diploma			-0.35***	-0.31***
Mother has some college			0.00	0.00
GPA 3 and up				-4.91
GPA 2-3				-5.13
GPA 1-2				-5.36
Verbal score				0.01
Math score				0.24***
/				
HS	-1.93***	-2.87***	-3.18***	-8.10
Some College	-1.38***	-2.26***	-2.56***	-7.46
Bachelor's	-0.90***	-1.75***	-2.04***	-6.91
Adjusted R^2				
Observations	1159	1159	1159	1159

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 29: LPM for Expectation Change from College to Less Than College: ELS

	(1)	(2)	(3)	(4)
Black	0.03**	0.01	-0.01	-0.10***
Hispanic	0.10***	0.08***	0.04***	-0.02*
Asian or PI	-0.05***	-0.05***	-0.07***	-0.06***
Native American	0.05	0.02	-0.00	-0.06
Multiple races	0.05**	0.03*	0.02	-0.01
Male	0.03***	0.02***	0.03***	0.02***
Family shocks		0.01	-0.00	-0.02*
Victimization shocks		0.02***	0.02***	0.01***
Low income			0.08***	0.05***
Mid income			0.03***	0.02**
Mother has no degree			0.19***	0.11***
Mother has HS diploma			0.14***	0.09***
Mother has some college			0.06***	0.03***
GPA: 3-4				-0.36***
GPA: 2-3				-0.27***
GPA: 1-2				-0.14***
Reading score				-0.00***
Math score				-0.01***
Constant	0.12***	0.08***	-0.01	0.80***
Adjusted R^2	0.01	0.02	0.07	0.15
Observations	7747	7747	7747	7747

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 30: Attainment Expectations by Expectations for Other Future Events, 75th Percentile: NLSY

	(1) All mean/sd	(2) Victim mean/sd	(3) Arrest mean/sd	(4) Death mean/sd	(5) Pregnancy mean/sd	(6) Drunk mean/sd
Coll exp 0-25	0.13	0.16	0.18	0.14	0.19	0.18
	(0.34)	(0.36)	(0.39)	(0.35)	(0.39)	(0.39)
Coll exp 25-50	0.18	0.22	0.26	0.22	0.26	0.19
	(0.38)	(0.42)	(0.44)	(0.41)	(0.44)	(0.39)
Coll exp 50-75	0.13	0.14	0.14	0.15	0.16	0.14
	(0.33)	(0.35)	(0.35)	(0.35)	(0.37)	(0.35)
Coll exp 75-100	0.56	0.48	0.41	0.49	0.39	0.49
	(0.50)	(0.50)	(0.49)	(0.50)	(0.49)	(0.50)
Par exp 0-25	0.14	0.18	0.20	0.17	0.21	0.19
	(0.35)	(0.38)	(0.40)	(0.37)	(0.41)	(0.39)
Par exp 25-50	0.25	0.31	0.30	0.30	0.30	0.27
	(0.43)	(0.46)	(0.46)	(0.46)	(0.46)	(0.44)
Par exp 50-75	0.11	0.10	0.10	0.09	0.11	0.11
	(0.31)	(0.30)	(0.30)	(0.29)	(0.31)	(0.32)
Par exp 75-100	0.50	0.42	0.39	0.44	0.37	0.43
	(0.50)	(0.49)	(0.49)	(0.50)	(0.48)	(0.50)
Observations	3546	673	797	825	823	854

Table 31: Ordered Probit for Student Expectations: NLSY

Exp: crime victim	0.10		0.22	0.19	0.17
Exp: arrest	-0.82***		-0.59***	-0.69***	-0.62***
Exp: death	-0.19		-0.32**	-0.29**	-0.26*
Exp: pregnancy	-0.78***		-0.64***	-0.56***	-0.51***
Exp: get drunk	0.05		0.07	0.07	0.11
Absent mother		0.00	0.00	0.00	0.00
Absent father		-0.22***	-0.21***	-0.08	-0.05
Changed schools		-0.19**	-0.15	-0.13	-0.09
Parent died		-0.27*	-0.23	-0.14	-0.15
Parent hospitalized		0.41***	0.40***	0.43***	0.42***
Parent jailed		-0.34*	-0.21	-0.18	-0.12
Parents divorced		-0.12	-0.12	-0.12	-0.12
Sibling count		-0.08***	-0.08***	-0.06***	-0.06**
Feels unsafe		-0.29***	-0.28***	-0.26***	-0.24***
Victim of crime		-0.09	-0.09	-0.09	-0.07
Demographics	No	Yes	Yes	Yes	Yes
SES controls	No	No	No	Yes	Yes
Mom's ed. controls	No	No	No	Yes	Yes
GPA controls	No	No	No	No	Yes
Observations	1958	1958	1958	1958	1958

Table 32: College Attainment on Expectations for Other Events: NLSY

	(1)	(2)	(3)	(4)	(5)
	College grad	College grad	College grad	College grad	College grad
Expect: victim of crime	-0.04	-0.06	-0.05	0.01	0.01
Expect: arrest	-0.22***	-0.09	-0.06	-0.04	0.01
Expect: death	-0.10*	-0.07	-0.07	-0.08*	-0.06
Expect: pregnancy	-0.23***	-0.11*	-0.00	0.02	0.04
Expect: get drunk	0.00	-0.01	-0.06*	-0.06*	-0.03
Coll exp 25-50		0.06**	0.04	0.04	0.04
Coll exp 50-75		0.23***	0.16***	0.14***	0.12***
Coll exp 75-100		0.40***	0.27***	0.25***	0.20***
Black			-0.06**	-0.02	0.02
Hispanic			-0.11***	-0.11***	-0.09***
Asian or PI			0.14*	0.14*	0.10
Native American			-0.05	0.05	0.02
Multiple races			-0.12	-0.11	-0.08
Male			-0.06***	-0.06***	-0.03
Low income			-0.16***	-0.11***	-0.10***
Mid income			-0.06*	-0.04	-0.04
Mother has no degree			-0.31***	-0.30***	-0.25***
Mother has HS diploma			-0.28***	-0.28***	-0.24***
Mother has some college			-0.19***	-0.18***	-0.16***
Break-in by 18				-0.06**	-0.03
Bullied by 18				-0.04	-0.04
Seen shooting by 18				-0.06**	-0.05*
Feels unsafe				-0.08***	-0.07***
Victim of crime				-0.01	-0.00
Ever homeless, 1997-2002				-0.15***	-0.13**
No mother or female guardian in HH				0.00	0.00
No father or male guardian in HH				-0.03	-0.01
Changed schools				-0.08***	-0.06*
Parent died				-0.07	-0.08*
Other family died				-0.02	-0.03
Parent hospitalized				-0.03	-0.03
Parent jailed				-0.08	-0.04
Parents divorced				-0.04	-0.04
Parent unemp				-0.00	0.02
Sibling count				-0.01	-0.01
GPA 3 and up					0.38***
GPA 2-3					0.14***
GPA 1-2					0.04
Constant	0.40***	0.10***	0.54***	0.72***	0.41***
Adjusted R^2	0.02	0.13	0.23	0.26	0.32
Observations	1954	1954	1954	1954	1954

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 33: Ordered Probit for Categorical GPA: ELS

	(1) Final GPA	(2) Final GPA	(3) Final GPA	(4) Final GPA
Final GPA				
Black	-0.69***	-0.55***	-0.20***	-0.20***
Hispanic	-0.51***	-0.43***	-0.13***	-0.11***
Asian or PI	0.12***	0.16***	0.16***	0.16***
Native American	-0.55***	-0.41***	-0.13	-0.13
Multiple races	-0.29***	-0.24***	-0.15***	-0.15***
Male	-0.33***	-0.33***	-0.39***	-0.40***
No mother in HH		-0.16***	-0.06	-0.06
No father in HH		-0.24***	-0.16***	-0.16***
Changed schools		-0.36***	-0.30***	-0.30***
Unsafe neighborhood		-0.16***	-0.08	-0.07
Feels unsafe		-0.33***	-0.10***	-0.10***
Moderate crime		-0.11***	-0.05*	-0.04
High crime		-0.23***	-0.12**	-0.12**
Reading test score			0.02***	0.02***
Math test score			0.04***	0.04***
Low income				0.01
Mid income				-0.01
Mother has no degree				-0.23***
Mother has HS diploma				-0.18***
Mother has some college				-0.15***
Adjusted R^2				
Observations	12606	12606	12606	12606

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 34: OLS for Senior GPA on Freshman GPA: NLSY

	(1) GPA Yr 4, Std	(2) GPA Yr 4, Std	(3) GPA Yr 4, Std	(4) GPA Yr 4, Std
Black	-0.46***	-0.33***	-0.13***	-0.12***
Hispanic	-0.29***	-0.24***	-0.11***	-0.07*
Asian or PI	0.12	0.11	-0.08	-0.10
Native American	-0.42*	-0.34	-0.13	-0.11
Multiple races	-0.24	-0.24	-0.17	-0.17
Male	-0.35***	-0.36***	-0.18***	-0.19***
No mother or female guardian in HH		0.00	0.00	0.00
No father or male guardian in HH		-0.19***	-0.10***	-0.08**
Changed schools		-0.06	0.01	0.01
Parent died		0.01	0.06	0.07
Other family died		0.00	0.03	0.03
Parent hospitalized		0.08	0.03	0.02
Parent jailed		-0.43***	-0.38***	-0.37***
Parents divorced		0.01	0.00	0.01
Parent unemp		-0.07	-0.05	-0.04
Sibling count		-0.03**	-0.01	-0.00
Break-in by 18		-0.07	-0.06	-0.06
Bullied by 18		-0.03	0.04	0.04
Seen shooting by 18		-0.11**	-0.02	-0.01
Feels unsafe		-0.11***	-0.04*	-0.04*
Victim of crime		-0.20***	-0.14**	-0.14**
Ever homeless, 1997-2002		-0.34*	-0.15	-0.16
GPA Yr 1, Std			0.58***	0.57***
Low income				0.01
Mid income				0.05
Mother has no degree				-0.19***
Mother has HS diploma				-0.15***
Mother has some college				-0.16***
Constant	0.35***	0.64***	0.17***	0.24***
Adjusted R^2	0.06	0.09	0.34	0.34
Observations	4076	4076	4076	4076

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 35: College Attainment

	(1) College	(2) College	(3) College	(4) College	(5) College	(6) College	(7) College
Coll exp 25-50	0.05**	0.04	0.06**	0.04	0.06**	0.06**	0.04
Coll exp 50-75	0.24***	0.16***	0.23***	0.16***	0.20***	0.20***	0.14***
Coll exp 75-100	0.42***	0.28***	0.40***	0.27***	0.36***	0.35***	0.25***
Black		-0.06**		-0.06**			-0.02
Hispanic		-0.11***		-0.11***			-0.11***
Asian or PI		0.15**		0.14*			0.14*
Native American		-0.04		-0.05			0.05
Multiple races		-0.12		-0.12			-0.11
Male		-0.06***		-0.06***			-0.06***
Low income		-0.16***		-0.16***			-0.11***
Mid income		-0.06*		-0.06*			-0.04
Mother no degree		-0.31***		-0.31***			-0.30***
Mother HS diploma		-0.28***		-0.28***			-0.28***
Mother some college		-0.18***		-0.19***			-0.18***
Expect: victim of crime			-0.06	-0.05		0.02	0.01
Expect: arrest			-0.09	-0.06		-0.04	-0.04
Expect: death			-0.07	-0.07		-0.07	-0.08*
Expect: pregnancy			-0.11*	-0.00		-0.05	0.02
Expect: get drunk			-0.01	-0.06*		-0.03	-0.06*
Break-in by 18					-0.05*	-0.05*	-0.06**
Bullied by 18					-0.03	-0.03	-0.04
Seen shooting by 18					-0.11***	-0.10***	-0.06**
Feels unsafe					-0.09***	-0.09***	-0.08***
Victim of crime					-0.01	-0.01	-0.01
Ever homeless, 1997-2002					-0.17***	-0.18***	-0.15***
No mother in HH					0.00	0.00	0.00
No father in HH					-0.08***	-0.08***	-0.03
Changed schools					-0.09***	-0.09***	-0.08***
Parent died					-0.10*	-0.09*	-0.07
Other family died					-0.03*	-0.03*	-0.02
Parent hospitalized					-0.03	-0.03	-0.03
Parent jailed					-0.08	-0.07	-0.08
Parents divorced					-0.03	-0.03	-0.04
Parent unemp					-0.02	-0.01	-0.00
Sibling count					-0.03***	-0.03***	-0.01
Constant	0.04***	0.49***	0.10***	0.54***	0.37***	0.40***	0.72***
Adjusted R^2	0.12	0.23	0.13	0.23	0.18	0.18	0.26
Observations	1954	1954	1954	1954	1954	1954	1954

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

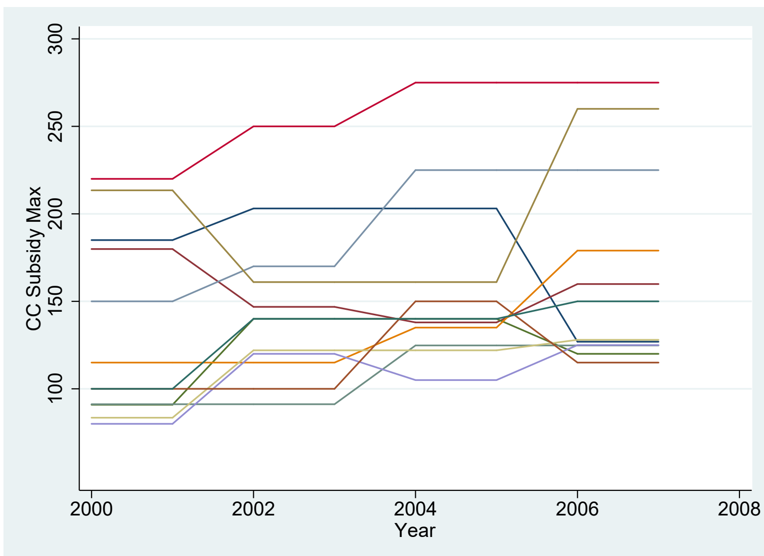
Table 36: 2SLS for College Attainment and Categorical Attainment Expectations

	(1)	
	College grad	Expect: college (cat.)
Expect: college (cat.)	0.14**	
Black	-0.04	0.30***
Hispanic	-0.08***	0.07
Asian or PI	0.05	0.35**
Native American	-0.03	0.05
Multiple races	-0.06	0.04
Male	-0.06***	-0.21***
Low income	-0.10***	-0.35***
Mid income	-0.03	-0.15**
Mother no degree	-0.26***	-0.72***
Mother HS diploma	-0.25***	-0.54***
Mother some college	-0.17***	-0.34***
No mother in HH	0.00	0.00
No father in HH	-0.02	-0.08*
Changed schools	-0.07**	-0.10
Parent died	-0.06	-0.13
Other family died	-0.03*	0.01
Parent hospitalized	-0.06*	0.19***
Parent jailed	-0.05	-0.17
Parents divorced	-0.04	-0.03
Parent unemp	0.01	0.05
Sibling count	-0.01	-0.04**
Break-in by 18	-0.05**	0.10
Bullied by 18	-0.02	0.00
Seen shooting by 18	-0.07***	-0.02
Feels unsafe	-0.06***	-0.19***
Victim of crime	-0.01	-0.07
Ever homeless, 1997-2002	-0.13**	-0.10
Expect: death	-0.09**	
Expect: arrest		-0.58***
Expect: pregnancy		-0.59***
Constant	0.36	4.35***
Adjusted R^2		
Observations	2509	

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Appendix for Chapter 3

Figure 9: Child Care Subsidy Levels by State



Each line represents the child care subsidy trajectory of a specific state or state group. Lines on this graph represent the eleven states in the top quartile of the standard deviation of their subsidy maximum over time.

Table 37: Summary Statistics

	All	Male	Female
Wage	15.27	16.90	13.56
Log wage	2.60	2.72	2.48
CC maximum	125.63	125.28	125.93
Union	0.15	0.19	0.10
Quit rate (pct)	0.31	0.24	0.37
Hispanic	0.16	0.16	0.15
Black	0.13	0.12	0.14
Other NWNH	0.04	0.04	0.05
Disability	0.13	0.13	0.14
Married	0.62	0.61	0.62
HS Grad	0.40	0.41	0.39
Some college	0.48	0.46	0.50
Age	41.43	41.01	41.83
Observations	48216	22051	26165

Table 38: Wages, Child Care Subsidies, and Union Concentration

	All	Male	Female	All	Male	Female
Female	-.232***	.	.	-.230***	.	.
Union member	.259***	.290***	.202***	.254***	.288***	.194***
CC rate	-.006	-.008	-.002	-.011	-.005	-.021*
Union concentration	.	.	.	.0009***	.0005	.002***
CCxUC	.	.	.	.0002	-.0002	.001***
Const.	2.149***	2.011***	2.099***	2.148***	2.013***	2.082***
Obs.	1020923	501045	519878	1020864	501033	519831

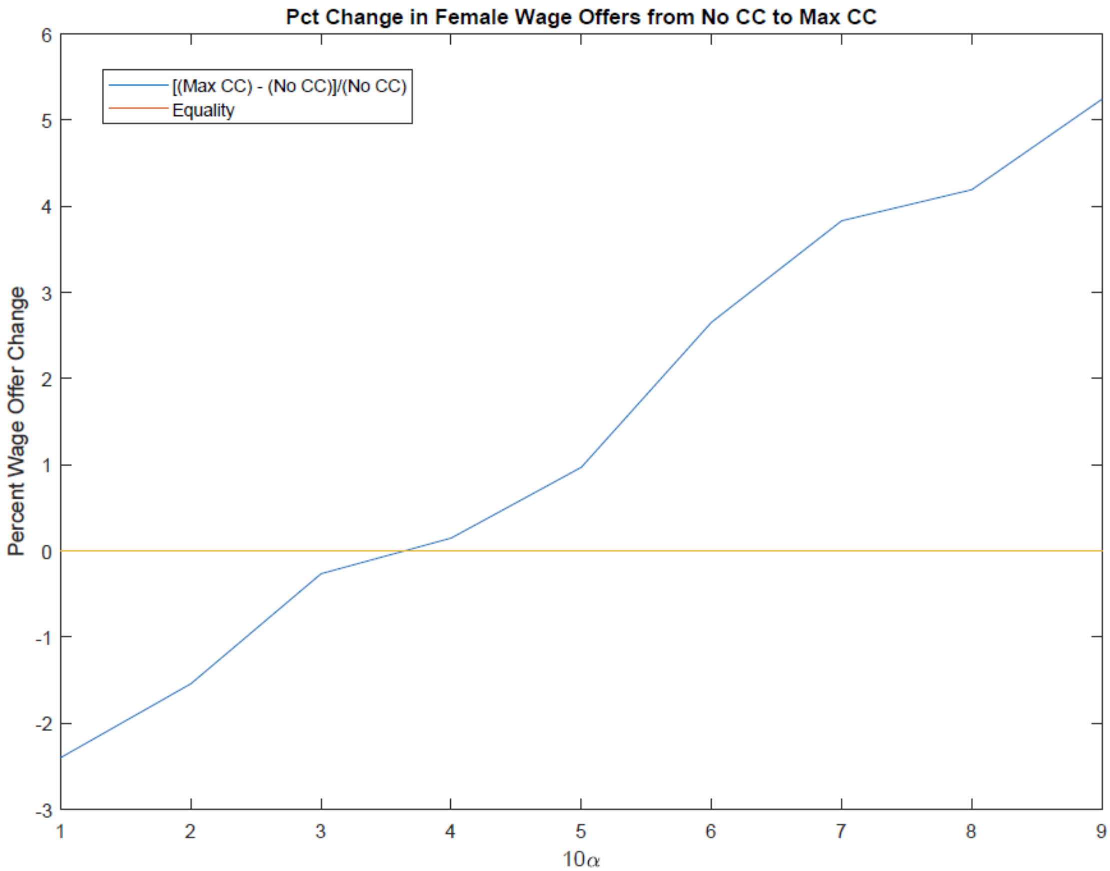
OLS estimates of Equation 3.7. Observations include all working sample members without a college degree. Covariates include race, marital status, education, age and age squared, occupational category, state-year policy variables for workers' compensation, unemployment insurance, and minimum wage, and fixed effects for year, state of residence, and occupation. $*p < 0.10$, $** \ p < 0.05$, $*** \ p < 0.01$.

Table 39: OLS WITH RIGHT-TO-WORK AND 2SLS

	First	All	Male	Female
Female	-.031***	-.244***	.	.
CC rate	-.003	-.009	-.003	-.020*
Union concentration	.008***	.	.	.
CCxUC	.00004	.	.	.
Union member	.	.323***	.314***	.411***
CCxUM	.	.018	-.021	.151***
Const.	-.092	1.883***	1.752***	1.825***
FS F-test	.	57.31	36.69	22.92
Obs.	996785	996785	490815	505970

2SLS estimates of Equation 3.8 (right panel). Observations include all working sample members without a college degree. Covariates include race, marital status, education, age and age squared, occupational category, state-year policy variables for workers' compensation, unemployment insurance, and minimum wage, and fixed effects for year, state of residence, and occupation. *$p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Figure 10:



Percent change in wage offers to female applicants between no-subsidy and maximum-subsidy scenarios, at different levels of α.

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Curriculum Vitae

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